A Formal Model for Fuzzy Ontologies

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Knowledge representation is one of the major research areas in artificial intelligence. Ontology, the specification of the concepts and objects in a particular domain, is becoming increasingly important among different models of knowledge representation. This is because ontology plays an indispensable role in handling automatic information processing as well as facilitating communications between software agents as the Semantic Web emerges.

Most of the existing ontology models can only specify concepts as crisp sets. However, we cannot avoid encountering concepts that are without clear boundaries, or even vague in meanings. Therefore, existing ontology models are unable to cope with many real cases effectively. With respect to a certain category, certain objects are considered as more representative or typical. Cognitive psychologists explain this by the prototype theory of concepts. As a result, this notion should also be taken into account to improve conceptual modeling. While there has been different research attempting to handle vague concepts with fuzzy set theory, formal methods for measuring typicality of objects are still insufficient.

Based on the prototype theory of concepts in psychology, we propose a formal model for fuzzy ontologies. This model is equipped with likeliness and typicality. Likeliness refers to

the extent to which an object is considered as an instance of a concept. Typicality refers to the representativeness of an object in a concept. This model not only enhances the effectiveness of conceptual modeling, but also brings the results of reasoning closer to human thinking. Owing to the importance of context in the interpretations of concepts and objects, our model also incorporates context-sensitivity, so as to provide more appropriate information according to the current context.

The model proposed in this thesis is based on in-depth investigation of the limitations of existing models, and findings in cognitive psychology. On top of this, the nature and differences between likeliness and typicality are thoroughly discussed. Not only does the model enrich the capability of ontologies to model fuzzy concepts, it also provides the mechanisms for determining typicality of objects as well as similarity between concepts in different context. We believe that this research is beneficial to future research on ontological engineering and knowledge representation in the Semantic Web.

摘要

論文題目：模糊本體的形式模型

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知識表示是人工智能研究的一個重要領域。在各種知識表示的模型中，本體，即對特定領域之概念和事物加以表述的方法，越來越有研究價值。自語義網面世後，本體變得更爲重要，因其在自動資訊處理，以及軟體代理之間的聯繫中，扮演著一個不可或缺的角色。

現時，多數的本體模型只能以樸素集合論的方式表述概念。可是，我們難免會遇上一些沒有明確分野，甚至意思模糊的概念。因此，現時的本體模型未能有效地滿足真正需要。在現實生活中，人總會認爲某些事物在某些特定領域中更具代表性。認知心理學家利用概念原型理論來解釋這種思維模式。在改良本體表述概念功能時，我們應該把此理論列入考慮之內。過往，曾有不少研究，嘗試以模糊集合理論來處理不清晰的概念，但對於本體表述事物典型性的處理方法，仍然顯得不足。

在這篇論文中，我們將會根據認知心理學家提出的概念原型理論，創立一個本體認知模型。此模型的特色，在於其擁有「類似歸屬度」及「典型歸屬度」兩種不同方法，計算物件在某類別的歸屬度。「類似歸屬度」是指某物件被歸類爲某概念的程度；「典型歸屬度」則用來量度某物件在某概念中的代表性。此模型不僅提高對概念和物件表述時的準確性，還使人工智能具有更接近人腦的推理能力。其次，在概念表述的過程中，語境脈絡會直接影響對概念和物件的詮譯，因此，本模型亦備有語意感應系統，以便根據當時的語境脈絡，提供更合適的資訊。

本論文提出的模型，一方面旨在提升現時本體模型研究的不足，一方面嘗試結合認知心理學的理論，意圖突破。而對於「類似歸屬度」及「典型歸屬度」的性質與差異，本論文都有十分詳細的分析。此模型能提升本體對模糊概念的表達能力，還提供在不同語境脈絡中分辨物件典型性以及概念類似度的決定機制。我們深信，本研究不但有利於本體工程學的未來發展，對語義網中知識表示的開拓亦有很大的啓發性。

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Chapter 1

Introduction

Since the seminal Dartmouth Conference in 1956 [73], artificial intelligence (AI) has grown into an independent field of research, drawing ideas as well as techniques from various fields, including philosophy, mathematics, computer science and engineering, economics, neuroscience, psychology and linguistics [94]. Within this large field of research, we have areas such as problem solving, searching, knowledge representation and reasoning, planning and decision making, statistical learning and neural networks, and robotics. There is no doubt that each of these areas has contributed to the advancement of artificial intelligence and has constituted a lot of useful applications, and each area has its own importance and significance. Here, we single out the area of knowledge representation.

Knowledge representation and reasoning is an area in artificial intelligence that concerns with how human knowledge, including abstract concepts, categories, method of classifications, procedural knowledge and relations between different entities, can be represented symbolically and in a structured way, so that a computer is able to manipulate the knowledge and other relevance information in an automated and efficient way, to perform reasoning tasks and to draw conclusions from known facts and knowledge [20]. We consider knowledge representation as one of the most important areas in the field of artificial intelligence. The ultimate aim of artificial intelligence is to realize intelligence in artificial entities such as computers. It has been a general view that human beings behave intelligently because of what they know and understand, and because of their ability to apply their knowledge to solve problems they encountered, to adapt to their continuously changing environment and to achieve their goals [20]. Therefore, to allow artificial software entities to behave intelligently or appear to have intelligence, it becomes inevitable that there must be effective and efficient ways for the representation of knowledge, which can be used as the basis for further intelligent tasks such as reasoning and decision making.

Research in the area of knowledge representation has generated quite a number of research topics, such as formal logics and logical reasoning, categorization and classification, analogical reasoning, and expert systems. Different methods and formalisms for representing human knowledge in computers in a structured and organized way have been developed, including first order logic, semantic networks, object-oriented models, description logics and ontologies, each with its own characteristics, advantages and limitations [20]. Among these formalisms, ontologies have attracted more and more attention in the last decade. Ontologies are now widely used as a means of conceptual modeling or domain modeling in various areas of application including knowledge management, natural language processing, e-commerce, information retrieval, bio-informatics, and the new emerging Semantic Web [40]. In particular, the Semantic Web [15] and the development of multiagent systems [119] have accelerated research on ontologies and ontological engineering.

In this thesis, we focus on the issue of knowledge representation with the use of ontologies in the context of the Semantic Web. We discuss the challenges facing knowledge representation in ontologies, identify problems as well as other desirable features of ontologies in the Semantic Web, and propose possible solutions to the problems and challenges. In the following sections, we give an overview of the Semantic Web and the use of ontologies as a knowledge representation formalism, and discuss the motivations as well as our objectives of our research work.

1.1 The Semantic Web and Ontologies

Ontology is originally a philosophical discipline [99]. It is a major and fundamental branch of metaphysics that tries to give a systematic explanation of being. It studies the problem of being, existence and their basic categorizations and relationships [40]. The word *ontology* has been adopted into the field of computer science, especially by researchers in artificial intelligence, to refer to the specification of the objects, properties and relations that one would encounter in a particular domain of discourse. One of the first definitions noted in [40] was given by Neches et al. [78]:

> *An ontology defines the basic terms and relations comprising the vocabulary of a topic area as well as the rules for combining terms and relations to define extensions to the vocabulary.*

Another mostly quoted definition of ontology was given by Gruber [43]:

> *An ontology is an explicit specification of a conceptualization.*

In summary, an ontology can be considered as a formal specification of basic concepts (terms), properties, relations between different entities, as well as rules governing the relations and interdependencies between the entities in a particular domain of discourse. Ontologies can be modeled with different knowledge representation formalisms and can be implemented in different formal languages. For example, at the beginning of the 1990s ontologies were modeled mainly by techniques based on frames and first-order logic [40]. In recent years, description logics have been used to model ontologies [10, 95]. It has also been suggested that other techniques that are widely used in software engineering and databases for conceptual modeling are also appropriate for building lightweight ontologies [40].

In recent years, the development of ontological engineering has been propelled and accelerated by the advancement of the World Wide Web and the emergence of the Semantic Web. As Berners-Lee et al. pointed out [15], ontology is an indispensable component of the Semantic Web. The Semantic Web enables more efficient information processing by describing resources on the World Wide Web with meta-data, so that the semantics of the resources as well as the relations between different resources can be understood by autonomous software agents which carry out information processing tasks on behalf of their human users. Ontologies play an important role in this technology, because they provide structures or models of known knowledge [68]. They specify the standard vocabularies for describing the available resources, and define the concepts and properties involved. With a suitable reasoning engine, software agents will be able to process information, discover implicit knowledge, or draw conclusions with the help of the definitions of concepts and relations in ontologies [68].

Since ontologies are so important in enabling the Semantic Web, the ability of ontologies to represent human knowledge of a particular domain in a precise and flexible way becomes a crucial aspect. In fact, there are quite a number of ontology models or ontology languages available when one wants to build an ontology [68]. In particular, it has been reported [64] that the DARPA Agent Markup Language and the Ontology Inference Layer (DAML+OIL) [50], the Resource Description Framework and Schema (RDF(S)) [63] and the Web Ontology Language (OWL) [74] are the three major ontology languages that are currently commonly used in the World Wide Web. These different ontology languages are characterized with different expressiveness and inference mechanisms. In general, a more expressive language or ontology model allows the ontology to model concepts and relations of higher complexity in a more efficient and flexible way. However, there is also tradeoff between expressiveness and tractability (computational complexity) in these models [20].

While these ontology models or languages provide standard methods for modeling knowledge of a particular domain, it is not difficult to note that these models suffer from certain limitations which avoid systems from providing better services in the Semantic Web. In this thesis, we investigate the limitations in conceptual modeling in existing ontology models, and propose possible extensions and solutions to these problems.

1.2 Motivations

There is no doubt that by using the ontology languages and models mentioned above we are able to model the known knowledge of a particular domain and are able to describe concepts and individual objects so that the underlying semantics becomes more explicit. For example, by using OWL, we can model the domain of publications, specify the common properties of the concept of "publications", define "magazines" and "books" as subclasses of "publications", so that they inherit all the properties of the concept [83]. Such an ontology will facilitate the task of processing information about publications with the help of autonomous software agents. Nevertheless, we notice that these ontology models are not without disadvantages or limitations.

1.2.1 Fuzziness of Concepts

One of the characteristics of these ontology models is that a set-theoretic approach is used to model concepts. Each concept is treated as a crisp set of individual objects, and complex concepts are constructed by using set operations such as union and intersections [74, 10]. However, if ontologies are used to model concepts that are frequently used in real life, the use of crisp sets in modeling concepts is obviously inadequate. Straccia [105] noted that there were limitations of this approach:

> "*...many useful concepts that are needed by an intelligent systems do not have well defined boundaries. That is, often it happens that the concepts encountered in the real world do not have a precisely defined criteria of membership, i.e. they are vague concepts rather than precise concepts.*"

What he referred to were concepts such as "tall", "heavy" or "high temperature" that do not have a strict and clear boundary between members and non-members. Currently, the commonly used ontology models are not able to handle these kind of vagueness in concepts. Some research work have proposed to employ fuzzy set theory (e.g. [103, 105, 102]) or probabilistic theory (e.g. [33, 52]) to solve this problem. In fact, providing a mechanism for handling fuzziness and vagueness of concepts in ontologies has been increasingly desirable and of great advantage [81, 102], because such mechanism allows systems to provide answers that are closer to human reasoning and human thinking, which are definitely beneficial to a human user.

1.2.2 Typicality of Objects

Besides the inability to handle fuzzy concepts, Brachman and Levesque mentioned in their book [20] about the limitations of crisp and precise logics:

> "*...when we try to emulate the more commonsensical kinds of reasoning that people do, we find that the crisp precision of classical logics may fall short of what we want...trying to represent what is known about a typical bird stretches our logical forms in one direction–not every bird has all of what we usually think of as the characteristics of birds in general.*"

From this description, we notice that besides what we call vagueness in concepts, we also have another issue of whether an individual object is typical or not. At first glance, such "typicality" of individual objects in concepts can be treated in the same way as in the case of vagueness, and in fact they can be both modeled by fuzzy set theory or probabilistic theory in some previous works (e.g. [35, 80]). Most of the existing approaches only focus on the fuzziness or vagueness of concepts but not on this typicality effect of categorizations. In fact, fuzziness and typicality are actually intrinsically different aspects of concepts. As mentioned in [54], we can identify two types of measures of an individual object's membership in a concept, referring to fuzziness and typicality. That different individual objects have different degrees of typicality (or prototypicality) in a certain concept is actually first studied in the field of cognitive psychology [91, 92, 100]. As works in cognitive psychology suggest, typicality is more a psychological effect than an objective decision of an individual's membership grade in a concept. It is found out that typicality of objects depends on the match of necessary properties as well as non-necessary properties [92]. For example, robins are generally considered as more typical birds than penguins [92]. This is probably due to the fact that birds are generally considered to be able to fly, but penguins do not. Hence, we can see that this is very different from, say, how we judge a certain temperature as "high" or not. Thus, typicality should be determined by a different mechanism from the one used to determine the fuzzy membership grade of an individual object. While it is desirable to model fuzziness of concepts in ontologies, the effect of typicality should not be overlooked. We believe that it is necessary to identify the differences between the two measures, so that we are able to come up with formal methods to model these two measures in ontologies.

1.2.3 Context and Its Effect on Reasoning

In addition, we notice that *context* is also a very important aspect in the process of reasoning. Context is generally understood to be the circumstances or situations in which certain event or action takes place [110]. Context is found to have influences on different cognitive tasks [93, 36]. In particular, the interpretation of a concept or the judgement of membership of an individual object in a concept can easily be influenced by the current context in which a person is situated [93]. Obviously, this is closely related to knowledge modeling in ontologies. Ontologies specify the definitions of concepts and relations between concepts and properties, and determine the requirements that an object should satisfy in order to be considered as a member of a concept. If an ontology is not sensitive to changes in context, a reasoning process based on the ontology will not provide satisfactory results. In fact, it has been discovered that the typicality of an individual object can also be different in different context [93]. Consider an example from [93]:

> "*...consider the sentence 'The bird walked across the barnyard.' 'Chicken' would seem to be more representative of 'bird' in this context than 'robin,' although in the absence of explicit context 'robin' is a more typical bird.*"

In existing ontology languages, one cannot specify the effect of changes in context on the concepts and properties, and only very few research projects attempt to provide a formal method to model context in ontologies [42, 41]. If ontologies are expected to provide the basis for reasoning about concepts and properties, and to assist agent communications and information sharing in the Semantic Web, it is obvious that the context in which the concepts and properties are mentioned should be taken into account, so as to provide more accurate descriptions of the situation, and to provide more accurate answers that are expected by human users.

The problems and limitations of current ontology models mentioned above suggest the need for a more flexible and expressive ontology model which is able to handle fuzziness of concepts, typicality of individual objects in concepts, and the effect of context on categorization and determining membership of individuals. Therefore, in this thesis, we investigate these challenges and propose a formal model for fuzzy ontologies to solve these problems.

1.3 Objectives

Ontology is an important component in the development of the Semantic Web. It is also useful in enhancing agent communications by providing agents with common terms and definitions of concepts. This thesis aims at investigating the problems and limitations of current ontology models, and suggesting methods to solve these problems. In particular, having identified the challenges mentioned in the previous section, this research aims at achieving the following objectives.

- Investigate how existing proposals model fuzziness and vagueness of concepts in ontologies, and identify their characteristics and weaknesses.

- Investigate the phenomenon of typicality of individual objects in concepts as studied in the field of cognitive psychology, and discuss how typicality can be formalized in an ontology model.
- Investigate the effect of context on different reasoning tasks, and explore how context can be modeled in an ontology so that the reasoning process can be sensitive to changes in context.
- Propose a formal model of ontology to model context, fuzziness of concepts and typicality of individual objects in concepts. This model should benefit knowledge representation in the Semantic Web and should enhance various services provided in the Semantic Web.

1.4 Contributions

This thesis reports our research work which investigates the problems and limitations of current ontology models in the context of the Semantic Web, and proposes a formal model for fuzzy ontologies to tackle the problems. Our work combines thorough background research, theoretical analysis and discussions. We summarize the contributions of our research work as follows.

- We carry out a thorough study of different ontology models, including existing ontology languages and models incorporating fuzzy set theory or probabilistic theory to handle fuzziness or uncertainty in concepts, and have identified the problems and limitations of these models.
- We investigate the nature of fuzziness in concepts as well as the psychological measure of typicality of individual objects in concepts. We have also examined the differences between the two measures.

- We propose a formal ontology model which includes methods for calculating the fuzzy membership grade, named likeliness, and typicality of individual objects in concepts. We have proposed a set of axioms that suitable functions for calculating the two measures should satisfy. The ontology model also formalizes context and provides mechanism for reflecting its influences on the two measures of membership of individual objects.

- We also carry out thorough analysis and discussions of the benefits and limitations of our proposed model of ontology. In particular, we mention some interesting properties of the model, and discuss its potential applications in the Semantic Web.

We expect that this work can benefit the future development of ontologies, and can be used to enhance knowledge representation in the Semantic Web. We also hope that our work can invoke future research that further investigates the role of fuzziness, typicality and context in ontology modeling and the Semantic Web.

1.5 Structure of the Thesis

This thesis is structured as follows.

Following this introductory section, Chapter 2 reviews the theoretical foundations of the topics involved in this thesis. These include the background of the Semantic Web, ontologies and Description Logics, fuzzy set theory and its use in modeling uncertainty in knowledge representation models. In addition, the chapter also mentions some psychological studies on the topic of concepts and categorizations, and some discussions of their implications on the development of ontologies.

Chapter 3 describes the details of the formal model of ontology proposed in this research. We start from the basic ideas in modeling of concepts and properties, and then go on to describe how we model membership grades (what we call "likeliness") and typicality of objects in concepts. We propose a set of axioms that an ontology model should follow when determining the likeliness and typicality of an object. We also propose a formal method to determine the similarity between two concepts, which may be useful in matching heterogenous ontologies in the Semantic Web. Moreover, we investigate the problem of context and the contextualization of ontologies. We describe how we model context in our proposed model, and describe how different contexts constitute different results of categorization or subsumption relations between concepts.

In Chapter 4, we present thorough discussions of the properties of the proposed model of ontology. Moreover, we discuss some interesting issues of the model, including the differences between likeliness and typicality of individual objects, and under what situation we should use likeliness and typicality for judging membership. In addition, we analyze both the advantages and limitations of our proposed model, as compared with other related projects in the literature. Finally, we discuss the potential applications of the model in the Semantic Web.

Finally, Chapter 5 draws conclusions, highlights the main research issues and major contributions of this research work. We also mention some future research directions and some of the research areas that can benefit from the work described in this thesis.

□ **End of chapter.**

Chapter 2

Background Study

This thesis investigates the problem of knowledge representation with the use of ontologies in the Semantic Web. This topic actually spans across quite a number of areas in the field of computer science. Firstly, this study requires a background of the development of the Semantic Web, which is an extension of the current World Wide Web. Secondly, the basic notions of ontology and descriptive ontological languages such as Description Logics are also required, because they provide a basis for the research work mentioned in this thesis. In addition, the mathematical tool of fuzzy set theory and its application in modeling vague and imprecise concepts in ontologies and Description Logics are also relevant. Besides, since we aim at developing a formal model of ontology which also takes into account how human users deal with concepts and categorizations, some basic ideas, such as the theories of concepts and the effects of context on categorization, from the studies of this topic within the field of cognitive psychology are also necessary.

In view of such a wide range of relevant topics, we organize and present in this chapter the necessary background information and related works which are essential to the understanding of the problems and proposed solutions mentioned in the rest of this thesis. In the following sections, we present the background information of the Semantic Web and its components, ontologies and Description Logics, fuzzy set theory, related studies in cognitive psychology, existing methods for modeling fuzziness and typicality, measuring semantic similarity and dealing with context in ontologies and other knowledge representation formalisms in general.

2.1 The Semantic Web

The Semantic Web is a vision which aims at creating a universal framework or infrastructure for information exchange on the World Wide Web by giving semantics (meanings) to resources so as to make them machine-readable or machine-understandable. The project was first proposed by Berners-Lee et al. [15]. The Semantic Web extends the abilities of the current World Wide Web by using technical standards, ontological markup languages and other related processing software.

Currently, contents on the Web are mainly marked up by HTML (Hypertext Markup Language) [85], whose tags govern only the presentation and layout of the content in a web document. However, HTML has very limited ability in describing the content of a document and giving semantics to blocks of text. This restriction severely limits automatic processing of web documents. Unless with advanced natural language processing algorithms [70, 51], the semantics of the content of the documents cannot be understood without human inspection. Hence, information gathering over the Web cannot be facilitated by using autonomous software agents.

In addition, nowadays information retrieval in the World Wide Web mainly relies on keyword-based search engines, such as *Yahoo!* and *Google.*[1] Despite their popularity, these search engines suffer from the following deficiencies [3]:

[1]Yahoo!: http://www.yahoo.com/; Google: http://www.google.com/

- **High recall, low precision.** The search result usually contains, along with the relevant pages, a lot of mildly relevant or irrelevant documents.
- **Low or no recall.** Sometimes the search result does not contain or does not return enough relevant documents.
- **Sensitivity to vocabulary.** The search results returns documents containing the keyword but not those which are semantically related to the query.
- **Results are single web pages.** When information spans across several documents, integration and extraction of the information must be done by the human user.

One may think that these problems will vanish as the technology of search engine improves. However, these problems are actually not due to the limitations of the technology of search engines, but are rather due to the limitations of the web documents themselves. The major problem is that currently web documents are not machine-accessible or machine-processable [3]. Without information on the semantics of the web documents, it is difficult to let computer software process the documents and extra useful information for the users.

The Semantic Web addresses this problem by using metadata called ontologies [44] specified in descriptive languages, such as RDF (Resource Description Framework) [63] and OWL (Web Ontology Language) [74], which are based on the customizable markup language XML (eXtensible Markup Language) [22], to markup resources on the Web. The standardized machine-readable descriptions allow content managers to add meaning to the content, thereby facilitating automatic information gathering and research by specialized software. Figure 2.1 shows the architecture of the Semantic Web proposed by Berners-Lee.[2]

[2]http://www.w3.org/2000/Talks/1206-xml2k-tbl/slide10-0.html.

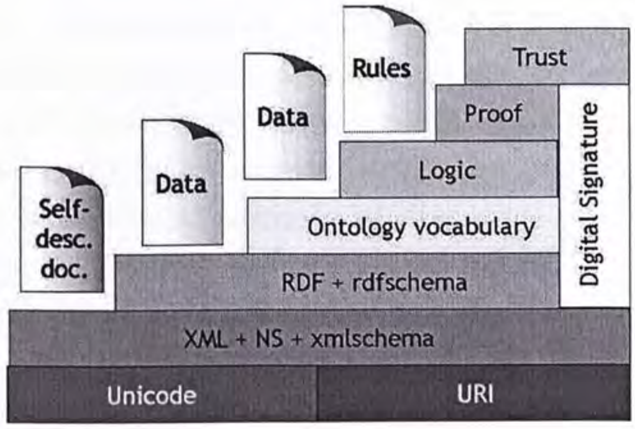

Figure 2.1: The Layered Structure of the Semantic Web proposed by Berners-Lee

The layers refer to different components of the Semantic Web. In the Semantic Web, each resource is given an URI (Uniform Resource Identifier). On top of this, we find XML which allows users to define their own vocabulary, and RDF which allows users to specify relations between resources. As we go up the layer, there are more expressive and powerful ontology languages, and also a logic framework which provides reasoning services on the concepts and properties defined in the ontologies. Finally the trust layer implements components, such as digital signature, which are used to ensure security and quality.

Since this thesis concerns the problem of representing knowledge in ontologies, we mainly deal with the ontology layer of the Semantic Web. More about knowledge representation in the Semantic Web and ontologies will be presented in the next section.

2.2 Ontologies

Ontology is originally a philosophical discipline, a major and fundamental branch of metaphysics, which studies the problem of being or existence and their basic categorizations and relationships [99]. The word *ontology* has been adopted into the field of computer science, especially by researchers in artificial intelligence and knowledge management, to refer to the specification of the objects, properties and relations that one would encounter in a particular domain of discourse [15, 20].

An ontology is usually defined as an explicit specification of conceptualization [43]. Ontologies can be used in the Semantic Web to provide semantics to resources so that they become machine-readable. Software agents are then able to access resources and communicate with one another based on the shared specification of the concepts.

An ontology generally consists of a taxonomy of concepts, a set of relations, a set of individuals (real objects), and possibly a set of inference rules for discovering implicit knowledge [15]. Throughout the history of the development of ontologies, there have been quite a number of definitions of ontology [31, 40]. To facilitate the discussions in this thesis, we adopt a rather concise definition of ontology as follows. Formally, an ontology O is a four-tuple

$$O = (C, P, I, R)$$

where C is a set of concepts, P is a set of properties of the concepts, which can be regarded as binary relations between concepts, I is a set of data instances of the concepts, representing real objects in the domain of interest, and lastly R is a set of rules, propositions or axioms that specify the relations between concepts and properties.

One of the characteristics of ontologies, which is different from traditional knowledge representation formalisms, is that the open world assumption (OWA) is employed. In other words, knowledge or beliefs that could not be concluded from the knowledge base is considered as unknown instead of false. This is an opposition of the traditional approach in which the close world assumption (CWA) is used. Such difference is due to the design issue that ontologies are generally used in a distributed environment such as multiagent systems and the Semantic Web [63, 74, 10]. If knowledge is stored in distributed ontologies, something that cannot be deduced from a single ontology may be inferred to be true with the help of the facts stored in other ontologies.

In the Semantic Web, different markup languages, such as RDF and RDF Schema [63], DAML+OIL [50] and OWL [74], are available for coding of ontologies. RDF stands for Resource Description Framework. It is a recommendation of the W3C and is intended for describing resources on the World Wide Web with meta-data. RDF is based on the idea that every objects are related to each other through a binary relation. For example, referring to Table 2.1 which shows an ontology adapted from [3], `involves` is a relation between a course and a lecturer.

Nevertheless, RDF and RDF Schema are limited to binary group predicates, subclass and property hierarchies. Quite a number of desirable features, such as range restrictions, disjointness of classes and cardinality restrictions, are not available [3]. These limitations in expressiveness initiated the development of a more powerful language, DAML+OIL, which eventually became the starting point for the W3C in defining the Web Ontology Language (OWL).

In general, it is desirable that an ontology language can fulfill both requirement of efficient reasoning support and convenience of expression [3]. However, this is not easily obtainable. This is because very expressive languages tend to have higher computational complexities which make efficient reasoning a more difficult task [10]. In view of this, OWL is divided into three sublanguages, namely OWL Full, OWL DL and OWL Lite, which provide different level of expressiveness. Table 2.2 shows a part of an ontology of traveling, adapted from [40] written in OWL

```
<rdfs:Class rdf:ID="lecturer">
  <rdfs:comment>
    The class of lecturers
    All lecturers are academic staff members.
  </rdfs:comment>
  <rdfs:subClassOf rdf:resource="#academicStaffMember"/>
</rdfs:Class>

<rdfs:Class rdf:ID="course">
  <rdfs:comment>The class of courses</rdfs:comment>
</rdfs:Class>

<rdf:Property rdf:ID="involves">
  <rdfs:comment>
    It relates only courses to lecturers.
  </rdfs:comment>
  <rdfs:domain rdf:resource="#course"/>
  <rdfs:range rdf:resource="#lecturer"/>
</rdfs:Property>
```

Table 2.1: Definitions written in RDF

with XML-based syntax.

On the other hand, the knowledge representation formalism of Description Logics [10] has a close relationship with ontologies. The two sub-languages of OWL, OWL DL and OWL Lite, can be viewed as expressive Description Logics and an ontology in these languages can be regarded as a knowledge base [49]. In the following section, we will give a brief review of Description Logics. As for more details on ontology development, readers can refer to the thorough review paper by Ding [31, 32].

```
<owl:Class rdf:ID="Flight"/>
  <rdfs:comment>A journey by plane</rdfs:comment>
  <owl:intersectionOf rdf:parseType="Collection">
    <owl:Class rdf:about="#Travel"/>
    <owl:Restriction owl:cardinality="1">
      <owl:onProperty rdf:resource="#flightNumber"/>
      <owl:allValueFrom rdf:resource="&xsd;integer"/>
    </owl:Restriction>
    <owl:Restriction>
      <owl:onProperty rdf:resource="#transportMeans"/>
      <owl:hasValue rdf:datatype="&xsd;string">
        plane
      </owl:hasValue>
    </owl:Restriction>
  </owl:intersectionOf>
</owl:Class>
```

Table 2.2: An excerpt of an ontology of traveling written in OWL

2.3 Description Logics

Description Logics (DLs) [10] is a knowledge representation formalism which allows reasoning about concepts and individuals. DLs have gained more and more attention as the Semantic Web technologies emerges, because they are considered as the theoretical support of logical reasoning services provided in ontologies.

The formalism of DLs is actually a family of languages, and different languages provide different constructors for construction of concepts and roles with different expressiveness. For example, the language $\mathcal{AL}$ [96], which stands for *attributive language*, provides a set of constructors that is useful in practical situations. Other more expressive languages can be created by extending $\mathcal{AL}$ by additional concept constructors. Here we give a brief description of the language $\mathcal{AL}$. We will follow the definitions and notations in [10].

In $\mathcal{AL}$, atomic concepts and atomic roles are the most elementary descriptions, based on which more complex concept description can be defined. In the following, we denote atomic concepts by capital letters A and B, atomic roles by capital letter R, individuals by small letters a and b, and concept descriptions (or simply *concepts*) by capital letters C and D. A concept can be constructed out of atomic concept descriptions by the following syntax rules:

$$
\begin{array}{rcll}
C, D & \longrightarrow & A| & \text{(atomic concept)} \\
 & & \top| & \text{(universal concept)} \\
 & & \bot| & \text{(bottom concept)} \\
 & & \neg A| & \text{(atomic negation)} \\
 & & C \sqcap D| & \text{(intersection)} \\
 & & \forall R.C| & \text{(universal quantification)} \\
 & & \exists R.\top & \text{(limited existential quantification)}
\end{array}
$$

In DLs, the semantics is provided based on the notion of interpretation. An interpretation $\mathcal{I}$ consists of a non-empty set $\Delta^{\mathcal{I}}$ representing the application domain, and an interpretation function, $\cdot^{\mathcal{I}}$, which maps every atomic concept A to a set $A^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$, and every atomic role to a relation $R^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$. For concept descriptions, the interpretation function is extended as follows:

$$
\begin{array}{rcl}
\top^{\mathcal{I}} & = & \Delta^{\mathcal{I}} \\
\bot^{\mathcal{I}} & = & \varnothing \\
(\neg A)^{\mathcal{I}} & = & \Delta^{\mathcal{I}} \setminus A^{\mathcal{I}} \\
(C \sqcap D)^{\mathcal{I}} & = & C^{\mathcal{I}} \cap D^{\mathcal{I}} \\
(\forall R.C)^{\mathcal{I}} & = & \{a \in \Delta^{\mathcal{I}} | \forall b.(a, b) \in R^{\mathcal{I}} \rightarrow b \in C^{\mathcal{I}}\} \\
(\exists R.\top)^{\mathcal{I}} & = & \{a \in \Delta^{\mathcal{I}} | \exists b.(a, b) \in R^{\mathcal{I}}\}
\end{array}
$$

In DLs, one can specify statements about concepts and roles by using terminological axioms. *Definitions* are specific terminological axioms and *terminologies* are sets of definitions. There are in general two types of terminological axioms, which have the forms

$$C \sqsubseteq D \quad (R \sqsubseteq S) \quad \text{or} \quad C \equiv D \quad (R \equiv S)$$

and are called *inclusion* and *equality* respectively. An interpretation $\mathcal{I}$ satisfies an inclusion $C \sqsubseteq D$ if $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$, and satisfies an equality $C \equiv D$ if $C^{\mathcal{I}} = D^{\mathcal{I}}$. Inclusion is also called *subsumption*, hence if $C \sqsubseteq D$, C is said to be *subsumed by* D. The set of definitions is called a terminology or a *TBox*.

In addition, a *world description* (*ABox*) contains *concept assertions* of the form $C(a)$, meaning that individual a is an instance of concept C, and *role assertions* of the form $R(a, b)$, meaning that individuals a and b are related to each other under the relation R. $C(a)$ is interpreted as $a^{\mathcal{I}} \in C^{\mathcal{I}}$, and $R(a, b)$ is interpreted as $(a^{\mathcal{I}}, b^{\mathcal{I}}) \in R^{\mathcal{I}}$. Hence, an *ABox* specifies the classification of individuals and relationships between individuals in the application domain. It should be noted that unlike classical databases in which the notion of "closed-world semantics" is adopted, ABoxes assumes an "open-world semantics" [77]. In other worlds, in DLs, knowledge represented in the knowledge base is not considered as complete knowledge of the domain of interest.

Finally, an interpretation $\mathcal{I}$ is said to be a *model* of a *TBox* if it satisfies all the terminological axioms in the *TBox*, and a *model* of an *ABox* if $\mathcal{I}$ satisfies all the assertions in an *ABox*. Together, if $\mathcal{I}$ satisfies both $\mathcal{T}$ and $\mathcal{A}$, it is a model of the knowledge base $(\mathcal{T}, \mathcal{A})$.

Description Logics have been considered as general languages for knowledge representation [77] from the very beginning, so DLs find application in many different areas. For example, DLs are especially effective for systems that need to handle concepts which could be organized along a hierarchical structure. Some examples of areas in which DLs are useful include database management [18], and expert systems used in medicine [101]. As the Semantic Web emerges, Description Logics have also found their important role in giving explicit semantics to resources on the Web [48]. For example, the developments of the ontology languages DAML, DAML+OIL and OWL are based on the research work on Description Logics. In addition, there are also proposals on incorporating fuzzy set theory into Description Logics to handle uncertainty and imprecision in concept modeling, which we will further discuss in later sections.

2.4 Fuzzy Set Theory

Fuzzy set theory was a mathematical theory first formalized by Zadeh [122] to handle uncertainty and imprecision in information systems. Fuzzy set theory can be considered as an extension of the classical (non-fuzzy) set theory, which is also generally called crisp sets in the literature [57]. In fuzzy set theory, membership of elements in a set is no longer limited to 0 (non-member) and 1 (member). Instead, the characteristic function of a set assigns a value within a specific range (usually from 0 to 1) to each element in the universal set to indicate the membership grade of each element in this set. Such function is called the membership function [57]. Formally, for a universal set X, the membership function of a fuzzy set A is denoted by

$$\mu_A : X \rightarrow [0, 1].$$

Fuzzy sets can be used to model concepts which do not have clear-cut boundaries. The concept "hot" is an example of such concept. There are no clear-cut boundaries such as a precise temperature above which the situation is considered "hot" and below which the situation is considered "not hot". With fuzzy set theory, the concept "hot" can be modeled as a fuzzy set, and the membership function can assign membership grade to different temperature values, where higher temperature values correspond to higher membership grade.

Operations on crisp sets have their counterparts in fuzzy sets, which are generalized version of the original operations. The three basic operations on crisp sets include complement, intersection and union. These three operations can be generalized to fuzzy sets in more than one way, as long as they satisfy certain axioms [57]. In particular, the operations proposed by Zadeh [122] is generally regarded as the standard operations. The following equations are commonly used to determine the membership function of the resultant set under standard complement, intersection and union respectively.

$$\begin{aligned} \mu_{\bar{A}}(x) &= 1 - \mu_A(x) \\ \mu_{A \cap B}(x) &= min[\mu_A(x), \mu_B(x)] \\ \mu_{A \cup B}(x) &= max[\mu_A(x), \mu_B(x)] \end{aligned}$$

Fuzzy sets allow systems to model uncertainty and imprecision by introducing graded membership degrees in sets. It also gives inception to other useful theories such as fuzzy logic and possibility theory. These theories find applications in many different domains. For example, fuzzy sets theory and fuzzy logic are used in controllers (e.g. [120, 121]), databases and information retrieval systems (e.g. [19, 27, 17]) and expert systems (e.g. [69, 97]). In recent years, fuzzy set theory and fuzzy logic have also been employed in ontologies for knowledge management and applications in the Semantic Web, we will describe these works, which are closely related to the problem we want to solve in this research work, in a later section.

2.5 Concepts and Categorization in Cognitive Psychology

In the Semantic Web, ontologies are used to specify the definition of concepts and relations between concepts. This information can be used to determine the subsumption relations between concepts, which results in a hierarchy of concepts. In fact, as Berners-Lee et al. mentioned [15], "*a large majority of the information we want to express is along the lines of 'a hex-head bolt is a type of machine bolt,'*" a concept hierarchy and subsumption relations between concepts are actually essential to the reasoning process and to the discovering of implicit information. Although some researchers may disagree and criticize the viewpoint as overly simplifying the situation (e.g. [37]), we believe that these aspects of concepts and categorization are fundamentally important to the building of more complex systems.

As such aspects are so important to the development of ontologies in the Semantic Web, we carry out some research on the basic ideas and the nature of concepts and categorization, in order to gain some insights for improving the current models. In fact, we discover two major themes which are explored in cognitive psychology: (1) how concepts are defined and represented, and (2) how concept hierarchies are formed. To enhance knowledge representation in the Semantic Web, we believe that it is beneficial to first obtain a general perspective of cognitive psychology. We hope the insights and inspirations revealed will be useful when we improve the current ontology model to enhance the representation and reasoning process, such that they will be more flexible in modeling human knowledge, as well as making the results closer to human thinking.

Here, in particular, we review several aspects which are closely related to the problems mentioned in our motivations of this research. The first aspect is the various theories of concepts, which discuss how concepts are mentally represented, and how people judge an individual's membership in a certain concept. The second aspect concerns the differences between fuzzy membership grades and the notion of typicality (prototypicality). In addition, we discuss how similarity between concepts is determined and mention related research in cognitive psychology. Finally, we present some research works on context and context effect, which are found to be influential in various cognitive activities, including classification and categorization.

2.5.1 Theory of Concepts

The Classical View

Concepts are abstract representation of objects existing in the world. Psychologists who study the human mind have long been investigating how concepts are represented in the human memory. Until the 1970s, the general view of concept held commonly among psychologists suggested that concepts are defined by singly necessary and jointly sufficient properties (features in psychological terms). This view is now generally referred to as the *classical view* [100]. The idea of this view can actually be traced back to the time of Aristotle's philosophically oriented studies of categories [4], which requires instances of concepts to meet a set of pre-defined conditions. For example, a square is defined as a shape with four sides equal in length and all angles measure 90 degrees.

The classical view sounds reasonable and intuitive. However, its claim that an object is either an instance of a concept (with the necessary properties) or it is not (missing one or more of the properties) has contradicted many experimental results in psychology. In particular, Rosch [91, 90] found that people judged different members of a category as varying in "goodness". For example, it has been found that people consider a sparrow as a much better example of birds than others such as ostrich or penguin, even though these are all classified as birds. The classical view is not able to give satisfactory explanation to this phenomenon with its simple and all-or-none principle. In fact, the "goodness" of the instance in a category is an important discovery because it plays a major role in different cognitive tasks such as sentence verification tasks [91] and ordering of instances [14].

The Prototype View

The findings mentioned above have motivated the development of the *prototype view* of concepts [92]. According to this view, a concept is represented by a prototype (an abstraction of the concept) in the human mind. The prototype of a concept consists of all the salient properties (properties that would appear in instances with high probability) that appear in the objects classified to this concept. The properties defining the prototype include both necessary and non-necessary properties. This is to model the fact that people tend not only to use necessary properties but also non-necessary properties to judge the "goodness" of an instance.

The view explains the existence of varying "goodness" of instances by the similarity between the instances and the concept prototype, and use the term *typicality* to refer to the degree of goodness. It has been found that typicality of an instance can be determined by the number of properties which are common to the instance and the concept prototype. For example, since most birds can fly, the property "*can-fly*" will probably appear in the prototype of the concept "*Bird*". Hence, birds that can fly will be judged as more *typical* than those that cannot.

Moreover, further studies of prototypes and typicality also suggest that properties in the prototype may not be of equal importance [90]. Some of the properties are considered more significant or important to the concept while others are considered less important. Thus, properties are very likely to be weighted according to their importance in the prototype of a concept.

Other Views

Although the prototype view has the ability to account for many different aspects of how concepts and properties are represented in the human mind, there are also other situations in which it fails to give a thorough explanation (see [100, 36]). Other proposals have also been developed to explain representation of concepts in the human mind. For example, the *exemplar view* [23, 46, 75], which is a modification of the prototype view, focuses on how prototypes (exemplars in this view's term) are formed during a learning process. In addition, the *schema view* [28] suggests using a schema instead of a prototype to represent the abstraction of a concept. However, since the prototype view gives the most detailed explanation of typicality, we will mainly use ideas from the prototype view in our research. The excellent review paper by Komatsu [60] on views of concepts can be referred to for more detailed explanation of these views.

2.5.2 Goodness of Example versus Degree of Typicality

On learning the phenomenon that many concepts have a graded structure (individuals have different membership grades in a concept), many will think of fuzzy set theory [122] when they try to model vagueness and uncertainty of concepts, because the theory is a well-known generalization of crisp sets with a characteristic function assigning membership grades to individual elements. However, there are in fact differences between fuzzy membership grades and typicality value, and it is inappropriate to model typicality by directly applying fuzzy set theory.

Armstrong, Gleitman and Gleitman [5] point out that typicality effects occur even in some concepts such as *odd number*, which has clear boundaries and definitions. They suggest that one should distinct membership from prototypicality (typicality). Kamp and Partee [54] also address the distinction between the two, and use c^e to represent the degree of membership in the extension of a concept (e stands for goodness of example), and c^p to represent the degree of typicality (p stands for prototypicality). While c^e measures whether or not and to what degree an instance is classified to a concept, c^p measures how representative or typical is an instance in a concept. It seems that typicality is rather a *psychological* measure than an objective decision of an individual's membership, because typicality effect is observed even in well-defined concepts.

From a logical perspective, it can also be seen that fuzzy set theory does not capture the essence of the Prototype Theory. As suggested in many empirical findings [92, 90], non-necessary properties are involved in determining typicality of instances. Instances that do not possess some of these properties are judged as less typical, but are not judged as non-member of the concept. Fuzzy set theory, though a generalization of crisp sets, still requires an element to attain membership greater than zero in each conjunct in order to attain an overall non-zero membership grade.

2.5.3 Similarity between Concepts

Similarity between concepts or objects is the focus of many cognitive psychology researchers, because it has been suggested that similarity is the basis of concept formation and categorization of objects [39], and plays a fundamental role in theories of knowledge and behaviour [111]. Similarity is generally understood to be the measure of how close two entities are related to each other in terms of the characteristics shared by them. In psychology, similarity is considered as the basis of several models of categorization, such as the exemplar model or the prototype model [88].

According to [111], theoretical analysis of similarity relations has been dominated by geometric models. Most theoretical and empirical analysis of similarity assume that objects can be adequately represented as points in some coordinate space with each dimension corresponds to one feature. A metric distance function δ is used to determine the distance between two objects. The smaller the returned value, the more similar are the two objects. In general, according to the geometric approach the metric distance function satisfies the following axioms:

$$\begin{aligned} \text{Minimality}: &\quad \delta(a,b) \geq \delta(a,a) = 0 \\ \text{Symmetry}: &\quad \delta(a,b) = \delta(b,a) \\ \text{The triangle inequality}: &\quad \delta(a,b) + \delta(b,c) \geq \delta(a,c) \end{aligned}$$

However, the author also points out that these three axioms for similarity may not be adequate or may not be true for determining similarity between concepts. In particular, [111] notes that there are empirical findings which suggest similarities between objects can be asymmetric, thus violating the axiom of symmetry. Furthermore, it also mentions that similarity is not necessarily transitive, such that although a and b are similar to each other and b and c are similar to each other, a conclusion which states that a and c are similar to each other may not be an appropriate one. The paper further suggests that similarity should better be measured by comparing the common and distinctive features (properties) of the objects or concepts involved.

We also note that the notion of similarity between concepts is not as straightforward as it appears to be. In particular, the judgement of similarity is subjected to changes of context, or the situation in which we perform a particular task. For example, Tavesky [111] mentions that when we do similarity assessment, "*we extract and compile from our data base a limited list of relevant features on the basis of which we perform the required task.*" Goldstone [39] also describes empirical findings of different psychologists and concludes that similarity is context-dependent. As context is considered as such an important aspect, we present a brief introduction to research works on context in the following section.

To conclude, similarity between concepts is an important topic, as it is closely related to categorization of objects and other reasoning tasks. When assessing the similarity between two concepts or two objects, a simple distance model which describes the two subjects as points in a coordinate space is insufficient. Rather, one must also take into account their common or distinctive properties, as well as the context in which the two subjects are situated.

2.5.4 Context and Context Effects

Context is one of the words that are used extensively in various fields. According to the Oxford Dictionary of English, context refers to the circumstances that form the setting for an event, statement, or idea; or the parts that immediately precede and follow a word or passage and clarify its meaning.

In cognitive psychology, context has its influence in many different aspects, including categorization [93], pronunciation of words [117, 116], text comprehension [21] and reasoning [26]. It is so commonly seen in different domains that psychologists coin the term "context effect" to refer to phenomena that result from changes in contexts. In addition, the judgement of similarity between concepts or objects is found to be dependent on the context of comparison [39]. Quite a number of researchers discover that when the context of a similarity comparison is explicitly manipulated in psychological experiments, wide variations in the resulting similarity assessment are obtained (e.g. [6, 107, 118, 93]).

In particular, Barclay et al. [12] mention an example in which context has its effect on interpretation of concepts. Given the two sentences: "The man lifted the piano" and "The man tuned the piano", people tend to associate the word "heavy" to the first sentence and the word "musical" to the second sentence. It is explained that the two sentences give different contexts, which result in the difference. People tend to focus on the weight of the piano when reading the first sentence, but focus on "produces music" when reading the second. Barsalou [13] also discovers that properties of a concept can be classified into two kinds, namely context-independent (CI) and context-dependent (CD). CD properties are significant only when the context is relevant. For example, that a basketball *can float* is only significant when the basketball is presented in the context related to water, such as swimming or riding a boat on the lake.

In addition, Roth and Shoben [93] investigate the effect of context in categorization. They discover that the typicality of instances as determined by the subjects varies as the context of the sentences presented to them changes. For example, normally people consider sparrow to be a typical bird. However, when presented the sentence "The bird walked across the barnyard", people will consider "chicken" to be a more typical bird in such context. They conclude that, if speaking in terms of the prototype view, such change in the typicality can be seen as the result of redistribution of the weights of the properties under different context. In other words, information presented in a particular context results in a different accessibility (weight) of the properties, and consequently a change in the typicality of different instances.

From the discussions and findings above, it can be concluded that context does play an important role in different reasoning tasks, especially when we talk about concepts, properties and similarity between concepts and objects. It is clear that without considering the current context of the reasoning task, the result is less likely to be an appropriate or an accurate one.

2.6 Handling of Uncertainty in Ontologies and Description Logics

Currently, ontologies are constructed by defining concepts and properties using one of the ontology languages. The concepts in these ontologies are interpreted as crisp sets. An individual is either considered as an instance of a concept or it is not. As the theoretical counterpart of ontologies, Description Logics are also restricted to handle crisp concepts [10].

To extend ontologies and description logics to handle fuzzy concepts, some researchers extend classical Description Logics with probabilistic theory or fuzzy set theory. For example, fuzzy set theory is used to extend ontologies to handle fuzzy concepts and assign membership degrees to instances [82, 30]. The fuzzy membership degrees are used to indicate the degree to which an instance is considered as a good example of a concept, and are mainly applied in retrieval of instances. In particular, [82] proposes a fuzzy ontology for retrieval of medical documents. It makes use of fuzzy membership value to indicate how likely an "overloaded" term (a term with several different meanings) is located in a particular location in the ontology.

As for the ontology languages, Ding and Peng [33] propose a method to extend the ontology language OWL with Bayesian networks (probabilistic theory) to represent uncertainty in ontologies. The work involves two steps to model uncertainty in OWL ontologies. Firstly, they augment OWL with probabilistic markups, so that conditional probabilistic information can be encoded in the ontologies. Secondly, a set of translation rules is defined to convert the ontology into a Bayesian network, which is ready for reasoning tasks. As a result, the ontology supports both common reasoning tasks as well as probabilistic reasoning. A similar extension on the language OWL is described in [103], in which fuzzy set theory is used to allow vague and imprecise concepts, such as "hot" and "fast", to be represented in OWL. The work starts from extending the description logic $\mathcal{SHOIN}$ by fuzzy set theory to provide reasoning capabilities for their proposed f-OWL.

There are in fact quite a lot of research works that concern with extending Description Logics, the theoretical counterpart of ontologies, to handle fuzziness and uncertainty in concepts. For example, Koller [59] proposes a probabilistic version of Description Logics. On the other hand, Straccia [105] combines fuzzy set theory and Description Logics and introduces fuzzy $\mathcal{ALC}$, in which concepts are interpreted as fuzzy sets. A reasoning procedure and an algorithm for deciding satisfiability in fuzzy $\mathcal{ALC}$ are also provided. It has been shown that fuzzy Description Logics are useful in multimedia information retrieval (MIR) [106], since it is common that there are inherent imprecision in multimedia object representation and retrieval. In addition, [47] further extends the expressiveness of fuzzy Description Logics by introducing fuzzy hedges. Fuzzy hedges are linguistic adverbs which modify the extent to which an adjective or a concept is used to describe certain situation. "Very", "more or less", "quite" are examples of hedges. In fact, Zadeh has proposed some formal methods to describe how hedges modify the membership function of a fuzzy set [123]. For example, the membership function of the concept "very hot" constructed by adding the hedge "very" to the concept "hot" can be obtained by raising the original membership function to a higher power: $\mu_{very\ hot}(a) = \mu_{hot}(a)^2$. This work extends this idea and proposes a framework of fuzzy Description Logics with hedges as concept (fuzzy set) modifiers.

These works extend the ability of ontologies to model concepts and increase the expressiveness of Description Logics. Since vague and imprecise concepts are very common in real life applications, modeling of these information in ontologies will provide more realistic, intelligent and effective reasoning results.

2.7 Typicality in Models for Knowledge Representation

Although the majority of knowledge representation models, such as those described in the previous section, that attempt to deal with fuzziness and uncertainty do not consider the intrinsic difference between the notion of membership grade and the notion of typicality, we actually found in literature that some works do focus on the importance of typicality and propose different methods to model it. In this section, we will give a brief review of the characteristics of these works.

Dubois, Prade and Rossazza [35] propose a frame-based object-centered representation (O.C.R.), which incorporates fuzzy set theory to model classes (concepts) in a domain of interest. This O.C.R. is proposed in order to allow various forms of plausible reasoning process of a human being, including typicality, uncertainty and vagueness. In this representation model, classes are intensionally described in terms of attributes (properties), of which the values are classified into two types, namely *allowed values* and *typical values*, where the ranges of these values are described by fuzzy sets.

In particular, this O.C.R. models typicality by employing the notion of typical range of attributes. The typical range $T(a, C)$ of an attribute a of the class C is the set of typical values that an instance of C can take for a. This range is represented by a fuzzy set, where typical values have higher membership grades than those that are less typical for the attributes. For example, in the class of "Birds", the attribute "way of locomotion" has a typical value "fly", but other less typical values, such as "walk" and "swim" also exist in the set of range in which they are assigned smaller values of membership grade.

The paper also describes the methods for determining subsumption (subclass) relations between classes. The authors argue that since a class is defined through the conjunction of its attributes and their ranges, the inclusion degree (subsumption degree) between two classes is defined as a conjunctive aggregation of the inclusion degrees of their ranges, which are fuzzy sets. They go on to describe how the certainty of membership degree, denoted by $N(C|x)$ of an object x in a class C can be determined. They call that the certainty of membership degree, rather than membership degree, because a particular object may not be precisely described by the attributes.

The O.C.R. supports a number of reasoning modes, including inheritance and classification. The use of typical range of values in describing the attributes allows the system to identify objects as possible typical members of a class. Thus it allows the system to reason in a way closer to human thinking and allows more flexible modeling of knowledge in a domain.

Tamma and Bench-Capon [109] present an extended ontology knowledge model which represents semantic information about concepts more explicitly. The authors argue that such ontology model is useful in describing agents in a multi-agent system, and is also useful in facilitating knowledge sharing by multiple agents. They mention that in order to recognize whether two concepts from heterogeneous knowledge sources are similar, one cannot only rely on the terms denoting them and on their descriptions, but need to have a full understanding of the semantics of the concepts.

In the extended model proposed, the semantic information which precisely characterizes the properties of a concept is enriched. In particular, an ontology model is enhanced by adding the following three characterizations of properties: (1) attribute behaviour over time, (2) modality, and (3) prototypical and exceptional properties. In particular, the authors mention that in order to have a full understanding of a concept, it is one of the important aspects that one recognize which properties are prototypical for the class membership, and which properties are the permitted exceptions.

The ontology model is a frame-based knowledge mode, and is based on the notions of classes, slots and facets. Classes are collections of objects sharing the same properties and are hierarchically organized. Slots, also known as attributes, are used to described concepts, and are themselves described by a set of additional constraints called facets. In this model, one of the facets is *value prototypes*, which specifies the prototypical values of the slot. As an example in the paper, when modeling the concept "blood pressure", one can specify that the prototypical value of "systolic blood pressure" is in the range of 90 to 130. By using this representation model, one can distinguish between properties that are necessary to the concept and properties that are only prototypical but not strictly required in the members of the class.

This model is useful in the way that it explicitly represents several important characterizations of properties, including prototypical values and exceptional values. This kind of semantic information of a concept allows knowledge to be modeled in a more flexible way, and enhances knowledge sharing in multiagent systems by facilitating ontology integration.

These two models go further than the other models which only provide one mechanism to model fuzziness and uncertainty in concepts. They provide additional methods for representing typical values of properties in different concepts, thus provide more flexible modeling of a domain, and allow results of the reasoning process to be closer to human reasoning and thinking.

Another formal approach commonly used to reason over typical and non-typical objects in logic is *default logic* [2, 86]. Default logic is a kind of non-monotonic logic which was proposed to formalize reasoning with default assumptions. It is possible to express facts that is true by default, but may have exceptional situations in which the facts can be false. Default logic introduces a new inference rule:

$$\frac{Prerequisite : Justification_1, ..., Justification_n}{Conclusion}$$

which states that if the prerequisite is deducible from the knowledge base, and if all the justifications are consistent with the current belief, then the conclusion can be said to be true. Hence, when reasoning about objects, if certain object is an exception which fails some of the justifications, the default conclusion will not be drawn.

While default logics and default reasoning provide an alternative approach to classical logics for handling typical and exceptional cases, it suffers from certain limitations. One restriction of such default logical reasoning is that one must list out all the possible justifications that an exceptional or non-typical object may violate. In addition, the reasoning process can only report objects that are inconsistent with the justifications, but cannot determine the degree to which it is a typical object with respect to a particular category. Nevertheless, it is considered as a useful tool comparing to classical logics in handling exceptional cases as it does not require all the exceptional cases to be listed out in the knowledge base.

2.8 Semantic Similarity in Ontologies and the Semantic Web

One of the major aspects that knowledge representation concerns is how concepts and knowledge can be symbolically represented and stored in a structured way in computers for future uses. Once this is done, we concern how these stored knowledge can be applied. One important task is to determine a degree or measure of semantic similarity between concepts [29].

With a measure of similarity, a system is able to obtain concepts that are similar or closely related to each other based on certain properties. This in fact has a wide range of application. For example, due to the distributive nature of the Semantic Web, there must be more than one ontology that describe similar concepts in a particular domain. When software agents using different ontologies want to communicate with each other, they have to match concepts in the two different ontologies [34, 53]. In this case, they must judge whether two terms refer to the same concept or two closely related concepts with the help of a measure of similarity. As in the case of information retrieval, determining semantic similarity between concepts is also an important task [113, 89], as it allows the retrieval system to identify similar concepts and provide the most relevant information to the users.

There are in fact quite a number of similarity measures used to assess the similarity between terms, concepts and ontologies, depending on the representation model used. For example, similarity between two terms can be determined by using a simple substring matching algorithm [61]. If concepts or objects are represented as vectorial data, with each dimension represents a distinctive feature, there are quite a number of distance measures for calculating the distance between two objects [67] (see Table). For example, two most commonly used distance functions are the Euclidian and weighted Euclidian distance functions. Similarity can then be obtained from these distance measures by first normalizing the values and then by using a decreasing function.

Name of Function	Distance Function
Euclidian	$d(x,y) = \sqrt{\sum_{i=1}^{p}(x_i - y_i)^2}$
Weighted Euclidian	$d(x,y) = \sqrt{\sum_{i=1}^{p}\alpha_i(x_i - y_i)^2}$

Table 2.3: Two commonly used distance measures

In ontology matching, similarity between two concepts is usually determined by the number of instances they share. For example, the Jaccard's coefficient [112] is used in the GLUE ontology matching system [34]:

$$Sim(A,B) = \frac{|x \in (A \cap B)|}{|x \in (A \cup B)|}.$$

This function compares the number of instances that belong to both concept A and concept B to the number of instances that belong to A or B only. The similarity between A and B will be higher as the number of instances shared by them increases.

In addition, [29] reviews and presents two types of semantic similarity measures, namely network distance models and information theoretical models. For network distance models, similarity is determined by the distance between the nodes in the ontology than corresponds to the concepts in question [84]. In order to reflect the edge distances, weights have been added to the edges between nodes in the ontologies to provide better assessment of similarity [56, 65]. Information theoretical models determine similarity by using information theory. This is based on the idea that similarity between two concepts can be judged by the degree to which they share information [29]. For example, the information shared by two concepts $c1$ and $c2$ can be approximated by the information content of the lowest superconcept $c3$ that subsumes them in the hierarchy [87]:

$$Sim(c1, c2) = -\log p(c3).$$

Although these measures are based on different approaches, it has been noted [29] that they can be viewed as variation of Tversky's [111] parameterized ration model of similarity:

$$Sim(X,Y) = \frac{f(X \cap Y)}{f(X \cap Y) + \alpha \times f(X - Y) + \beta \times f(Y - X)}$$

where $f(\cdot)$ is a function which compares the properties or shared instances of the concepts X and Y.

2.9 Contextual Reasoning

The theme of formalizing context in knowledge representation system has generated quite a number of research works. Among all of these, McCarthy [72] was the first to propose formalizing context in intelligent systems. He aims at introducing contexts as abstract mathematical entities with properties useful in artificial intelligence. He introduces the notation *ist(c,p)* to denote the assertion that a proposition p is true in context c. In addition, Giunchiglia [38] uses context as a means of formalizing the idea of localization, which takes "*context to be a set of facts used locally to prove a given goal plus the inference routines used to reason about them.*" Some subsequent efforts in formalizing context in logical languages include [24, 1]. These works focus on how context can be formally represented in a knowledge representation system, and how reasoning processes can accommodate changes in context.

As research and development of the Semantic Web proceed, an increasingly important issue in the use of ontologies in the Semantic Web is how context can be modeled. In particular, [79] mentioned two issues:

- How should an ontology be interpreted in specific, changing contexts?
- How can ontologies incorporate the notion of context?

The first issue concerns how the concepts, properties, and judgement of membership of individual objects are interpreted differently when there is a change in the context of the reasoning tasks. The second issue concerns how context can be formally represented in an ontology. In this thesis, since we focus on knowledge representation in ontologies and the Semantic Web, we will review several projects which focus on the relation between context and ontologies, and how context affects the reasoning process in ontologies and the Semantic Web.

Grossi et al. [41, 42] propose a theoretical framework to handle context in the language of Description Logics. The framework is developed for modeling situations such as "concept A is a kind of concept B in context C". The framework involves a contextual taxonomy model in which a set of models represents a set of different contexts. Subsumption relations between concepts only hold in specific contexts. The papers give an example describing different situations in which bicycles are counted or are not counted as vehicles. The framework is novel in the sense that it provides a formal semantics for contextualized subsumption expressions as well as the possibility of describing operations (such as combination or abstraction) on contexts. The work takes the first step to formalize context in Description Logics.

On the other hand, a logical extension called Context Description Framework [55] to the existing Resource Description Framework (RDF) has been proposed. The authors argue that properties has some sense in a certain context, which they specify the differences through the context tolerance range. They define context of a statement (a triple in RDF) as a set of other statements, which describe a certain condition of an environment. To accommodate this change, a contextual range for a property is added to a statement predicate. Thus, a statement in CDF becomes a quadruple. In CDF, the schema of RDF is extended by adding concepts such as `TrueInContext`, `cdfs:Container` and `cdfs:Statement` so that contextual information can be specified. The CDF is also augmented with probabilistic components. With this framework, multilevel contextual dependence can be described and Bayesian reasoning are also possible in the framework of RDF.

□ **End of chapter.**

Chapter 3

A Formal Model of Ontology

As described in chapter 2, existing ontology models generally adopt a set-theoretic model, and concepts are usually interpreted as crisp sets. Some of the newly proposed models make use of fuzzy set theory to provide a graded membership of individual objects in different concepts. However, the graded membership of individual objects observed in empirical findings in psychological experiments, known as typicality, is actually quite different from the graded membership modeled by fuzzy set theory. It seems that even though some projects introduce methods to describe typical values of certain properties, the main characteristics of Prototype Theory and typicality have never been captured.

In view of the inadequacy of the existing models of ontology, we propose in this thesis a novel theoretical framework for representation of individual objects and concepts in an ontology. This model of ontology is an extended model in the sense that concepts are interpreted as fuzzy sets rather than crisp sets, and formal methods for calculating the fuzzy membership degree and typicality of an individual object in a concept are included. Moreover, we develop a set of axioms which outline the requirements of a suitable similarity function which can be used to determine the similarity between different concepts. Lastly, we provide a formal method for modeling context and a mechanism for contextualizing an ontology.

In this chapter, we will describe in details the definitions, axioms and properties of this formal model of ontology. We start with the rationale based on which we design this formal model.

3.1 Rationale

Although there are quite a number of different definitions of ontology [40], it is generally agreed that the function of an ontology is to give a formal specification of different concepts in the domain of interest. Hence, it is inevitable that concept definitions are specified in terms of a set of requirements. In many models, such as RDF and OWL, these requirements are called properties. In our formal model, we follow this line of thought that concepts are defined by sets of necessary and sufficient properties. However, seeing that such approach is inadequate to represent graded membership and typicality of individual objects in concepts, we adopt a more general model of concept in this framework by extending existing models in two steps.

Firstly, we extend the model by (1) adding weights (a real number between 0 and 1) to properties that define a concept, and also by (2) using a real number between 0 to 1 to represent the extent to which an individual object possesses a certain property. For example, we can denote, using this model, that the property "high speed" is a very important property of the concept "Sports Car" by giving the property a weight of, for example, 0.9, and denote that a particular sports car possesses the property "high speed" to a degree of, for example, 0.7, which is a function of its maximum speed. Based on these two extensions, we develop a formal method to determine an individual's membership grade in a concept, which we give the name ***likeliness*** [7, 9].

Secondly, we further extend the model by formalizing the idea of prototype and typicality of objects in concepts. We suggest a method to construct a prototype for a concept, which can be used to determine the ***typicality*** of individual objects in concepts [7, 9]. It should be noted that we intentionally design two measures for judging the membership of an object in a concept. This is because, as we have discussed in the previous chapter, *typicality* is quite different from *goodness of example* in a concept. Therefore, we try to make clear this distinction between the two measures in our model of ontology. More discussions on this will follow the description of the proposed model.

Finally, we develop a framework to model ***context*** within the model of ontology proposed, so that an ontology constructed according to this model will be context-sensitive and will be able to provide more accurate answers by taking the context of the current tasks into account [8].

Before going into the details of the formal model of ontology, it should be noted that while we adopt ideas from the Prototype Theory in psychology, we realize that there are actually quite a number of suggestions in the field of psychology on how the Prototype Theory can be formally represented [100]. Thus the model proposed in this thesis should not be considered as a formalization of any particular description of the Prototype Theory, but should be considered as the formalization and implementation of the general ideas of the Prototype Theory in ontological engineering.

To facilitate the description of the proposed model, we will use examples to illustrate the ideas and properties of the model. In particular, concept definitions will be written in Description Logics, and explanation will be given when the notations are different from those included in classical Description Logics as described in Chapter 2.

3.2 Concepts

The basic elements of this ontology model are concepts. Intuitively, concepts are abstract representation under which real objects are grouped based on the properties they possess. The properties serve as the requirements for being considered as an instance of a concept. In this model, a weight is associated with each property in a concept to indicate the importance of that property. For individuals, each of them possesses a set of properties and a value is also associated with each property to indicate the degree to which the individual possesses the property.

In the following discussions, we will employ the definition of an ontology we present in Chapter 2. An ontology O is a four-tuple $O = (C, P, I, R)$, where C is a set of concepts, P is a set of properties of the concepts, I is a set of data instances of the concepts, and R is a set of rules, propositions or axioms that specify the relations between concepts and properties.

Definition 1. *A* ***concept*** $x \in C$ *is a fuzzy subset of the set* I *of individual objects, with a membership function* μ_x *assigning each instance* $a \in I$ *a membership grade in this concept.*

3.3 Characteristic Vector and Property Vector

To formally represent concepts and properties in an ontology, we propose two mathematical notations to represent how properties characterize concepts, and how individuals possess different properties to different extent. Firstly, each concept is characterized by a *characteristic vector*. A characteristic vector is defined as a vector of real number in the range of 0 to 1, in which each element corresponds to the weight of a different property.

Definition 2. *A* ***characteristic vector*** $\vec{c}_x$ *of a concept* x *is a* *vector of real numbers,*

$$\vec{c_x} = (c_{x,1}, c_{x,2}, ..., c_{x,n}), 0 \leq c_{x,i} \leq 1$$

where n is the total number of properties.

For an individual, a value of 1 of an element in the characteristic vector means that the property is essential to the concept, while a value of 0 means that the property is not required in the definition of the concept. For example, we can define the concept of "Sports Car" with the following characteristic vector:

$$\vec{c}_{SportsCar} = (0, 1, 1, 0, 0.8, 0)$$

where the non-zero property weights correspond to the properties "has wheels", "fast" and "streamlined" respectively.

Secondly, each individual object is characterized by a *property vector*. A property vector of an individual is a vector of real number in the range of 0 to 1, in which each element corresponds to the degree to which the individual possesses a property.

Definition 3. *The* ***property vector*** $\vec{p_a}$ *of an individual object a is a vector of real numbers,*

$$\vec{p_a} = (p_{a,1}, p_{a,2}, ..., p_{a,n}), 0 \leq p_{a,i} \leq 1$$

where n is the total number of properties.

For example, we can describe a certain car with the following property vector:

$$\vec{p}_{carA} = (0.5, 1, 0.7, 0, 0.9, 0)$$

where the non-zero degrees of possession correspond to the degrees of possessing the properties of "expensive", "has wheels", "fast" and "streamlined" respectively.

In proposing these two vectors for the characterization of concepts and individuals, we make the assumption that properties are independent of each other (though we are aware that some properties may be closely related to each other, which we will discuss about this in later sections), and the set of properties is finite.

3.4 Subsumption of Concepts

Concepts in an ontology are generally arranged in a hierarchy such as in OWL [74], and subsumption of concepts are determined by examining whether the set of properties of one concept is a subset of that of another concept. In some other models, a concept is considered as subsumed by another concept if there are specialization of the range of values of attributes, or if there are addition of new attributes [35]. In our proposed model of ontology, we generalize this idea and subsumption of concepts can be determined by comparing the weights in the characteristic vector. For a concept to be considered as subsumed by another concept, it should be characterized at least by all the properties of the latter, and with higher weights for each of these properties.

Definition 4. *For two concepts x and y, x is said to be* ***subsumed by*** *y, denoted by $x \sqsubseteq y$, if and only if $c_{x,i} \geq c_{y,i}$ for all $i = 1, 2, ..., n$.*

The definition of subsumption implies two situations that one concept x can be considered as a sub-concept of another concept y. In the first case, two concepts are defined by the same set of properties, but x weights some properties as more important than they are in y. In the second case, x has a larger set of defining properties than y. Both situations are intuitively easy to understood, this is because a sub-concept should impose more requirements of properties on an individual than its super-concept. It can also be easily seen that this is in fact a generalization of the idea of subsets of properties.

For example, if we assume four concepts A, B, C and D, and four properties p_1, p_2, p_3 and p_4 in an ontology, with the following four characteristic vectors for the four concepts:

$$\begin{aligned}
\vec{c}_A &= (0, 0, 1, 0.5) \\
\vec{c}_B &= (0, 0.4, 1, 0.8) \\
\vec{c}_C &= (1, 0, 1, 1) \\
\vec{c}_D &= (0.8, 0.4, 1, 0.8)
\end{aligned}$$

then by Definition 4, we can easily conclude the following subsumption relations:

$$D \sqsubseteq B \qquad D \sqsubseteq A \qquad B \sqsubseteq A \qquad C \sqsubseteq A$$

In addition, we define the notion of sub-concepts, super-concepts, defining properties and possession of properties as follows.

Definition 5. *If $x \sqsubseteq y$, then x is said to be a **sub-concept** of y.*

Definition 6. *If $x \sqsubseteq y$, then y is said to be a **super-concept** of x.*

Definition 7. *The set of properties P_x that includes all properties having a weight greater than zero in the characteristic vector of a concept x is said to be the set of **defining properties** of x, or x is said to be **defined by** the set P_x. Formally,*

$$P_x = \{k_i | k_i \in P \wedge c_{x,i} > 0, i = 0, 1, 2, ..., n\}.$$

Definition 8. *The set of properties P_a that includes all properties having a degree greater than zero in the property vector of an individual a is said to be the set of **properties possessed by** a. Formally,*

$$P_a = \{k_i | k_i \in P \wedge p_{a,i} > 0, i = 0, 1, 2, ..., n\}.$$

3.5 Likeliness of an Individual in a Concept

One important function of an ontology is to allow one to determine whether a given individual object is an instance of a particular concept. In traditional models of ontology which employ a set-theoretic approach, this is usually determined by examining whether the instance is a member of every conjuncts in the concept definition [10]. In our formal model of ontology, since we allow degrees of possession of properties and weights for different properties in concepts, an individual object has a membership degree in a concept, rather than a single state of member or non-member.

The first type of membership measure that we want to handle is fuzzy membership grade of individuals. We call this degree of membership as *likeliness*. The measure of likeliness of an individual determines whether or not and to what degree an individual is classified to a concept according to the defining properties. This actually corresponds to the measure of "goodness of example" mentioned by Kamp and Partee [54].

Definition 9. *In an ontology $O = (C, P, I, R)$,* ***likeliness*** *of an individual object a in a concept x is determined by a function which returns the degree to which a is considered as an instance of x:*

$$\lambda_x : I \longrightarrow [0, 1]$$

To determine the degree of likeliness of an individual object in a concept, a function is required. In general, a function for calculating the degree of likeliness is a function of the characteristic vector of the concept and the property vector of the individual object. While it is possible to have different functions for likeliness, we argue that likeliness should satisfy the following axioms.

Axiom 1. *An individual a has a degree of likeliness of 1 in a concept x if and only if $c_{x,i} > 0 \rightarrow p_{a,i} = 1$ for all $i = 1, 2, ..., n$.*

Axiom 2. *An individual a has a degree of likeliness of* 0 *in a concept* x *if and only if* $c_{x,i} > 0$ *and* $p_{a,i} = 0$ *for some* $i \in [1, n]$.

Axiom 3. *For a concept* x*, and two individuals* a *and* b*, if for some* j *such that* $c_{x,j} > 0$, $p_{a,j} > p_{b,j}$ *and* $p_{a,i} = p_{b,i}$ *for all* $i \neq j$*, then* $\lambda_x(a) > \lambda_x(b)$.

Axiom 4. *For two concepts* x *and* y*, and an individual* a*, if for some* j *such that* $c_{x,j} \geq c_{y,j} > 0$, $1 > p_{a,j} > 0$, $c_{x,i} = c_{y,i}$, $p_{a,i} > 0$ *for all* $i \neq j$*, then* $\lambda_y(a) \geq \lambda_x(a)$.

Axiom 5. *For two concepts* x *and* y*, and an individual* a*, if for some* j *such that* $c_{x,j} \geq c_{y,j} > 0$, $p_{a,j} = 1$, $c_{x,i} = c_{y,i}$*, and* $p_{a,i} > 0$ *for all* $i \neq j$*, then* $\lambda_y(a) = \lambda_x(a)$.

Axioms 1 and 2 state the boundary conditions for the degree of likeliness. In words, an individual must possess all the properties with non-zero weight in the characteristic vector in order to be an instance of the concept. To have a likeliness of one, the degree of a property in the property vector should be one whenever that is a defining property of the concept. On the other hand, if the individual does not possess one or more of the defining properties, its likeliness will be zero.

Axioms 3 to 5 state how the degree of likeliness is varied when degree of possession and property weights change. Firstly, if one individual possesses a property that the concept assumes non-zero weight to a degree higher than another individual does, then the former will attain a higher degree of likeliness than the latter. This is justified by the fact that the first individual satisfies the requirement to a higher degree. On the other hand, Axiom 4 states that an individual should achieve a higher degree of likeliness in a concept that places lower weights on properties than the individual possesses than another concept that places higher weights on the properties. This axiom is justified because when a property is given higher weight, it is considered as more important and thus there is a more strict requirement on an individual, and therefore the likeliness of an individual is lowered. Lastly, an exception is described in Axiom 5, which is when the degree of the property in question in the property vector is equal to 1. In this case, since the individual already possesses the property to a full extent, it does not matter to what extent the property is important to the definition of the concept, hence it makes no differences between the degree of likeliness of the individual in the two concepts.

Any function will be considered suitable for the calculation of likeliness of an individual object in a concept, as long as it satisfies the above axioms. Here, we present a possible function that can be used as the membership function of a concept to determine the degree of likeliness of an individual.

$$\lambda_x(a) = \min_i \{l_i\} \tag{3.1}$$

where

$$l_i = \begin{cases} p_{a,i} + (1 - c_{x,i}) \times (1 - p_{a,i}) & \text{if } c_{x,i} > 0, p_{a,i} > 0 \\ 0 & \text{if } c_{x,i} > 0, p_{a,i} = 0 \\ 1 & \text{if } c_{x,i} = 0 \end{cases}$$

Since $p_{a,i}$ is in the range of [0,1], $\lambda_x(a)$ is also in the range of [0,1]. The idea of this function is to scale the degrees ($p_{a,i}$'s) in the property vector of an individual by using the property weights ($c_{x,i}$'s) in the characteristic vector of the concept. According to this function, a degree will be scaled to a larger value if the corresponding weight is smaller, and will remain the same if the weight is 1. The minimum value among these degrees will be obtained to be the likeliness of the individual. This calculation is justified because lower weight corresponds to a looser requirement on that property, and hence the degree should be less decisive in calculating the membership grade. On the other hand, using this function the degrees of the most important properties are most likely to affect the membership grade. It can be easily verified that this function satisfies the axioms 1 to 5 mentioned above.

For example, we can apply this function to calculate the likeliness of the individual "carA" in the concept "SportsCar", which we have mentioned earlier in this chapter:

$$\begin{aligned}
\vec{c}_{SportsCar} &= (0, 1, 1, 0, 0.8, 0) \\
\vec{p}_{carA} &= (0.5, 1, 0.7, 0, 0.9, 0) \\
\lambda_{SportsCar}(carA) &= \min\{1, 1, 0.7, 1, 0.92, 1\} \\
&= 0.7
\end{aligned}$$

The function of likeliness can be used as the membership function of a concept to determine the extent to which an individual object is considered as an instance of a concept:

$$\mu_x(a) = \lambda_x(a)$$

3.6 Prototype Vector and Typicality

As suggested in psychology [92, 54], *typicality* is a measure of how representative or typical an individual is in a particular concept. Typicality is measured based on the number of properties that are shared by most of the individuals of the concept, which usually include non-necessary properties of a concept [100]. In other words, the characteristic vector alone is not enough to handle typicality because it only contains information of necessary properties of a concept. Therefore, we introduce here a new data structure called *prototype vector*.

As typicality of an individual is determined by its similarity to the prototype of a concept [90], we need to first construct a prototype for the concept. According to [100], properties in the prototype "*are salient ones that have a substantial probability of occurring in instances of the concept.*" In other words, the weights of the properties in the prototype depend on the saliency of the properties in the instances. Therefore, to construct the prototype of a concept, we must first obtain information about the most common properties in the instances. In this model, we construct the prototype of a concept based on this general idea of prototype. However, we rely on weights of properties in the sub-concepts instead of using the saliency of properties. The reason is twofold. Firstly, information is most probably stored in a distributive manner and instances may be scattered in different ontologies. If the weights are dependent on the instances, then the prototypes in different ontologies will tend to be different to a large extent, and the prototype will be inaccurate if the number of instances available is small. Moreover, weights of properties in the sub-concepts indicate the importance of the properties. This implies that representative examples will possess properties of higher weights. This also gives us information about the saliency of properties. Therefore, the prototype of a concept, represented by a prototype vector, is defined as follows.

Definition 10. *The* ***prototype vector*** $\vec{t_x}$ *of a concept* x *is a vector of real numbers,*

$$\vec{t_x} = (t_{x,1}, t_{x,2}, ..., t_{x,n}), 0 \leq t_{x,i} \leq 1 \tag{3.2}$$

and is determined by the following equation:

$$\vec{t_x} = \sum_{s \in S \cup \{x\}} \alpha_s \times \vec{c_s} \tag{3.3}$$

where S *is the set of sub-concepts of* x *as determined by Definition 4,* α_s *is a weight (0 to 1) for the sub-concept* s *and* $\sum_{s \in S \cup \{x\}} \alpha_s = 1$.

The elements in the prototype vector of a concept are actually the weighed averages of the weights of properties in the characteristic vectors of the concept and its sub-concepts. Hence, if a property is weighted high in more sub-concepts, its weight in the prototype vector will be higher. In the most general case, it is simply the averages of the weights if all α_s's are having the same value. When the degrees of importance of the sub-concepts can be known, then the α_s's can be used to reflect their importance when calculating the prototype vector. It should be noted that in constructing this prototype vector, we assume that the available sub-concepts are the only sub-concepts of the concept in question, hence we make the close world assumption, instead of the commonly used open world assumption in ontologies. This is understandable because no prototype vector can be constructed if an unknown factor is included in calculating the average of the property weights.

Typicality is determined by a "*weighted feature (property) sum*" [100], which means that typicality is reflected by the summation of the weights of the properties that the individual possesses. In our model, this involves first matching the properties in the prototype vector of a concept and the property vector of an individual. We denote the typicality function of a concept by τ_x:

Definition 11. *For an ontology $O = (C, P, I, R)$, **typicality** of an individual object a in a concept x is determined by a function which returns the degree to a is considered as a typical instance of x according to the prototype of x:*

$$\tau_x : I \longrightarrow [0, 1]$$

In general, the function of typicality of an individual object in a concept is a function of the prototype vector of the concept and the property vector of the individual object. With a similar approach used in determining the function of likeliness, we formulate the following axioms which a function for typicality should follow.

Axiom 6. *An individual a has a degree of typicality of* 1 *in a concept* x *if and only if* $t_{x,i} > 0 \rightarrow p_{a,i} = 1$ *for* $i = 1, 2, ..., n$.

Axiom 7. *An individual a has a degree of typicality of* 0 *in a concept* x *if and only if* $t_{x,i} > 0 \rightarrow p_{a,i} = 0$ *for* $i = 1, 2, ..., n$.

Axiom 8. *For a concept* x*, and two individuals* a *and* b*, if for some* j *such that* $t_{x,j} > 0$*,* $p_{a,j} > p_{b,j} \geq 0$ *and* $p_{a,i} = p_{b,i}$ *for all* $i \neq j$*, then* $\tau_x(a) > \tau_x(b)$.

Axiom 9. *For two concepts* x *and* y*, and an individual* a*, if for some* j *such that* $t_{x,j} > t_{y,j} > 0$*,* $p_{a,j} > 0$ *and* $t_{x,i} = t_{y,i}$ *for all* $i \neq j$*, then* $\tau_y(a) > \tau_x(a)$.

Axioms 6 and 7 specify the boundary cases of typicality. According to the Prototype Theory [100], there are two major issues in determining the typicality of an individual in a concept:

1. An individual does not need to possess all the properties in the prototype.

2. An individual is considered as more typical if it has more properties of the concept prototype.

Hence, an individual's typicality will be zero only when it does not possess any of the properties in the prototype.

Axiom 8 states the influence of degrees in the property vector on typicality. If two individuals possessing the same set of properties, and one possesses the properties which appear in the prototype to a higher degree than the other, then the former will attain a higher typicality than the latter. Moreover, if the first individual possesses more properties in the prototype than the other, the former individual should attain a higher typicality. This axiom is justified to be in line with the Prototype Theory because in both cases the former individual is considered as more similar to the concept prototype.

The last axiom states that an individual should achieve a higher degree of typicality in a concept that places less weights on properties that the individual possesses than another concept that places more weights on the properties. This is justified because when a property is given more weights, it is more important in the prototype, thus an individual will attain lower typicality in such concept than in another concept which does not consider that property to be that important.

Similar to the discussions on the calculation of likeliness, we present a possible function for calculating an individual's typicality in a concept. The typicality of an individual a of a concept x, denoted by $\tau_x(a)$ is given by:

$$\tau_x(a) = \frac{\vec{p_a} \cdot \vec{t_x}}{\sum_{i=1}^{n} t_{x,i}} \tag{3.4}$$

where $\vec{p_a}$ is the property vector of individual a, $\vec{t_x}$ is the characteristic vector of concept x, and n is the total number of properties or the length of the vectors.

This function is actually the scalar product of the two vectors normalized by the total number of properties. It is based on the similar idea of using scalar product to determine resemblance mentioned in [66]. The higher the resultant number (in the range [0,1]), the more typical is the individual. It should be noted that even though the individual does not possess all the properties having a weight greater than zero in the prototype vector, its typicality value in that concept can still be greater than zero. Therefore, typicality is different from likeliness, which, though also varies between a range of zero to one, is only greater than zero if the individual possesses all the properties having a weight greater than zero in the characteristic vector.

3.7 An Example

In order to illustrate how the proposed ontology model in this research, including likeliness and typicality, can be used to provide more realistic results, we present an example involving an ontology of birds. Firstly, let us assume that we have the following excerpt of an ontology of birds written in Description Logics.[1] In the *TBox*, we assume:

$$\begin{aligned}
\mathsf{Bird} &= \mathsf{Vertebrate} \sqcap \mathsf{HasWings} \sqcap \mathsf{HasFeathers} \\
\mathsf{Sparrow} &= \mathsf{Bird} \sqcap \mathsf{CanFly} \sqcap \mathsf{SeedEater} \\
\mathsf{Parrot} &= \mathsf{Bird} \sqcap \mathsf{CanFly} \sqcap \mathsf{HasCurvedBeak} \\
\mathsf{Robin} &= \mathsf{Bird} \sqcap \mathsf{CanFly} \sqcap \mathsf{CanSing} \\
\mathsf{Ostrich} &= \mathsf{Bird} \sqcap \mathsf{CanRun}
\end{aligned}$$

In addition, we assume that the following individual objects are defined in the *ABox*.

$$\mathsf{Sparrow(s1)}\ ,\ \mathsf{Parrot(p1)}\ ,\ \mathsf{Robin(r1)}\ ,\ \mathsf{Ostrich(o1)}$$

From the *TBox*, a reasoning task of subsumption will discover the following subsumption relations between the concepts defined.

$$\begin{aligned}
\mathsf{Sparrow} &\sqsubseteq \mathsf{Bird} \\
\mathsf{Parrot} &\sqsubseteq \mathsf{Bird} \\
\mathsf{Robin} &\sqsubseteq \mathsf{Bird} \\
\mathsf{Ostrich} &\sqsubseteq \mathsf{Bird}
\end{aligned}$$

The above ontology of birds can be extended according to our formal model of ontology by first adding weights of properties to the definition of the birds. We indicate the weight of each

[1]This example is only for illustration and is not meant to be a complete and exact definition of the animals involved.

property with a number in subscript.

$$
\begin{aligned}
\mathsf{Bird} &= \mathsf{Vertebrate}_1 \sqcap \mathsf{HasWings}_1 \sqcap \mathsf{HasFeathers}_1 \\
\mathsf{Sparrow} &= \mathsf{Bird} \sqcap \mathsf{CanFly}_1 \sqcap \mathsf{SeedEater}_{0.8} \\
\mathsf{Parrot} &= \mathsf{Bird} \sqcap \mathsf{CanFly}_1 \sqcap \mathsf{HasCurvedBeak}_1 \\
\mathsf{Robin} &= \mathsf{Bird} \sqcap \mathsf{CanFly}_1 \sqcap \mathsf{CanSing}_{0.8} \\
\mathsf{Ostrich} &= \mathsf{Bird} \sqcap \mathsf{CanRun}_1
\end{aligned}
$$

From the above definitions, a set of properties can be obtained: *is-vertebrate*, *has-wings*, *has-feathers*, *can-fly*, *is-a-seedeater*, *has-curved-beak*, *can-sing* and *can-run*. There are a total of eight properties and therefore the characteristic vectors contain eight elements, presumably in the order listed above. Note that the property of "*is-a-bird*" can be reduced to properties defining the concept "Bird".

Furthermore, we assume that the property vectors of the sparrow $\mathsf{s1}$ and the ostrich $\mathsf{o1}$ are as follows.

$$
\begin{aligned}
\vec{p}_{\mathsf{s1}} &= (1, 1, 1, 0.9, 1, 0, 0, 0) \\
\vec{p}_{\mathsf{o1}} &= (1, 1, 1, 0, 0, 0, 0, 0.8)
\end{aligned}
$$

In addition, we obtain the prototype vector of the concept "*Bird*" from the definitions using equation 3.3:

$$\vec{t}_{\mathsf{Bird}} = (1, 1, 1, 0.75, 0.2, 0.25, 0.2, 0.25)$$

While it is obvious that the degrees of likeliness of the two individuals in the concept "Bird" is 1 (they possess all the properties of the concept "Bird" and the weight of each of these properties is 1), typicality for $\mathsf{s1}$ and $\mathsf{o1}$ can be obtained by using the typicality function 3.4:

$$
\begin{aligned}
\tau_{\mathsf{Bird}}(\mathsf{s1}) &= 0.833 \\
\tau_{\mathsf{Bird}}(\mathsf{o1}) &= 0.688
\end{aligned}
$$

This result suggests that the sparrow $\mathsf{s1}$ is a more typical bird than the ostrich $\mathsf{o1}$.

With the traditional approach, we can only determine whether an individual object is an instance of a concept, but cannot determine whether one object is more typical than another with respect to a certain concept. This example illustrates that with the model of ontology proposed in this research, it is possible to discover the relative typicality of the individual objects. In addition, the model provides the flexibility that one can choose to order the individual objects by their likeliness or by their typicality. More discussions on the characteristics of this model will be given in Chapter 5.

3.8 Similarity between Concepts

In using ontologies for representing domain knowledge, determining a degree of semantic similarity between concepts is an increasingly important task [29]. With a proper method to measure similarity, users and agents are able to discover similar concepts by using the information that is available in the ontologies. In the Semantic Web this is particularly useful, because potentially relevant information can be discovered by judging the degree of similarity between the concepts and individual objects defined in the ontologies. Besides, ontologies in the Semantic Web has a distributed and heterogeneous nature [115]. In other words, there will not be a centralized and standardized ontology for all applications in the Semantic Web, but rather every domain of application will have their own specialized ontologies. Hence, when agents need to assess information from different ontologies, there must be some methods for mapping concepts from one ontology to another ontology. In such case, a mechanism for determining similarity between concepts will be very useful.

We develop a similarity measure for determining the degree of similarity between concepts in our ontology model by first defining the similarity function and then by formulating a set of axioms that such function must satisfy. Similarity is also a very topic interested by cognitive psychologists. We will therefore refer to studies in cognitive psychology as we formulate the measure of similarity, because they provide useful insight to this issue.

We first give the definition of the similarity function.

Definition 12. *The* ***similarity function*** *of concept x, $\sigma_x(y)$, computes the degree that concept y is similar to x:*

$$\sigma_x : C \longrightarrow [0,1]$$

It should be noted that this similarity function is defined as the degree that concept y is similar to concept x, instead of the degree of similarity between x and y. This is because we follow the idea that similarity is not necessarily symmetric [111]. Therefore, the notation $\sigma_x(y)$ is used, instead of the commonly used one (e.g. $Sim(x, y)$) which takes two concepts as parameters for the function. In addition, like many other measures of similarity [29], our similarity function returns a value between 0 and 1.

We follow the basic ideas on measuring similarity between concepts presented in [111], and come up with the follow axioms that a function of similarity $\sigma_x(y)$ should satisfy if it is to be used for measuring similarity in our model of ontology.

Axiom 10. *For two concepts x and y, if $\vec{c}_x = \vec{c}_y$, then $\sigma_x(y) = \sigma_y(x) = 1$.*

Axiom 11. *For two concepts x and y, if $\vec{c}_x \cdot \vec{c}_y = 0$, then $\sigma_x(y) = \sigma_y(x) = 0$.*

The first three axioms for the function of similarity concern the boundary cases. According to axiom 10, the function will only return 1 if the two concepts are characterized by the same set of properties and each property weight is the same. In other words, the two concepts are the same and cannot be differentiated from each other based on the defining properties. The similarity function returns 0 if the two concepts do not have any common properties. Hence, the degree of similarity is wholly dependent on the set of properties defining the concepts. The following four axioms further describe how the number of properties and property weights affect how similar a concept is to another one.

Axiom 12. *For three concepts x, y and z, if for some j such that $c_{x,j} > c_{y,j} > 0$, $c_{z,j} > 0$, and $c_{x,i} = c_{y,i}$ for all $i \neq j$, then $\sigma_z(x) > \sigma_z(y)$.*

Axiom 13. *For three concepts x, y and z, if for some j such that $c_{y,j} > c_{z,j} > 0$, $c_{x,j} > 0$, and $c_{y,i} = c_{z,i}$ for all $i \neq j$, then $\sigma_y(x) > \sigma_z(x)$.*

Axiom 14. *For three concepts x, y and z, if for some j such that $c_{y,j} = 0$, $c_{x,j} > 0$, $c_{z,j} > 0$ and $c_{x,i} = c_{y,i}$ for all $i \neq j$, then $\sigma_z(x) > \sigma_z(y)$.*

Axiom 15. *For three concepts x, y and z, if for some j such that $c_{y,j} = 0$, $c_{x,j} > 0$, $c_{z,j} = 0$ and $c_{x,i} = c_{y,i}$ for all $i \neq j$, then $\sigma_z(y) > \sigma_z(x)$.*

To describe the above axioms, we first explain the notion of subject and referent as mentioned in [111]. When we make statements in the form of "y is similar to x", y is called a subject and x is called a referent. Such statement is actually directional. We usually focus on properties that are salient in x and determine the similarity of y to x ($\sigma_x(y)$) by the presence of these properties in x. For example, let us consider the sentence "Bats are similar to birds." In this sentence, we can identify the subject (Bats) and the referent (birds). When making such declaration, we focus on the properties of the referent, such as being able to fly, and then determine that the subject is similar because it possess these properties. If we exchange the subject and referent in this sentence, the similarity may be changed because the saliency of the properties in question may be changed. In our model, the saliency of the properties in a concept is determined by the property weights in the characteristic vector.

Axiom 12 states that if y has a property weighted higher than z (both y and z are subjects), and if this property is a defining property of x (a referent), y will be more similar to x than z will be to x. Axiom 13, on the other hand, states that if y weights a property higher than z (both y and z are referents this time), and if this property is a defining property of x (a subject), then x is more similar to y than to z. In other words, a concept x is more similar to another concept y if properties common to each other are weighted higher in both concepts.

In addition, the number of common and distinctive properties also affects how similar a concept is to another one [111]. Axiom 14 states that if concept x has a non-zero weight for a property which is weighted zero in another concept y, and at the same time this concept is a defining concept of z, x will be more similar to z than y is to z. In other words, if two concepts have more common properties, the degree of similarity will be higher. Furthermore, Axiom 15 describes the opposite situation in which x has more distinctive properties than y when compared to z (the referent), in such case y will be more similar to z, because y and z have less distinctive properties.

We define the similarity function for measuring similarity between concepts. However, the method can also be applied to comparing individual objects in the ontology. The current similarity function depends on the characteristic vectors of the two concepts involved. If we want to measure similarity between individual objects, a new similarity function can be defined in a similar way by replacing the characteristic vectors by the property vectors of the objects involved.

Finally, we present a possible function for calculating the degree of similarity of y to x, $\sigma_x(y)$, which satisfies the above axioms. Firstly, we define the following notations:

$$\vec{c'}_x = (c'_{x,1}, c'_{x,2}, ..., c'_{x,n})$$

where

$$c'_{x,i} = \begin{cases} 0 & \text{if } c_{x,i} > 0 \\ 1 & \text{if } c_{x,i} = 0 \end{cases}$$

In addition,

$$\begin{aligned} \vec{w}_{y,x} &= (w_{y,x,1}, w_{y,x,2}, ..., w_{y,x,n}) \\ \vec{v}_{y,x} &= (v_{y,x,1}, v_{y,x,2}, ..., v_{y,x,n}) \end{aligned}$$

where

$$\begin{aligned} w_{y,x,i} &= c_{y,i} \times c_{x,i} \\ v_{y,x,i} &= c_{y,i} \times c'_{x,i} \end{aligned}$$

The function is given by:

$$\sigma_x(y) = \frac{\alpha(\vec{w}_{y,x} \cdot \vec{c}_x)}{\sum_{i=1}^{n} c_{x,i}} - \frac{\beta(\vec{v}_{y,x} \cdot \vec{c'}_x)}{\sum_{i=1}^{n} c'_{x,i}}$$

where α and β are real numbers such that $\alpha > 0$, $\beta > 0$ and $\alpha + \beta = 1$. The two parameters α and β actually control the weights of the two parts, one measures the common properties of the two concepts, and another one measures the distinctive properties of the two concepts. It can be easily verified that this function satisfies all the axioms discussed above.

3.9 Context and Contextualization of Ontology

As we have discussed in Chapter 2, context is a topic of research that is of interest in various fields, including both computer science and cognitive psychology. In cognitive psychology, it has been found out that context plays an important role in various cognitive and reasoning tasks. Perception, understanding and decision-making are dependent on context [36], and are not invariant across different contexts. On the other hand, research communities in computer science, especially artificial intelligence, are also very interested in context. One of the objectives of artificial intelligence is to make computers draw conclusions based on known facts and knowledge [94]. Context provides the background information and other objects related to the event or action taking place, and hence, by taking the current context into account, computers will acquire a better understanding of a particular situation and will be able to return more appropriate results with respect to the available information.

The term "context" is frequently seen in computer science literature. However, as noted in [16], the meaning of the term is mostly left to the readers' understanding and its usage is implicit and intuitive. [16] adopts the definition of context from the Free On-line Dictionary of Computing: context is "*that which surrounds and gives meaning to something else*".[2] In general, we agree that context is intuitively understood as the surrounding entities that provide more information or meanings to the entity that we are focused on. In addition, we want to highlight the two views on the distinction between ontologies and contexts noted in [98]. The first view is that ontologies are shared models of a domain and contexts are local views of a domain. The second view is that ontologies are manual effort of modeling a domain, while contexts are system generated models of a domain.

In order to model context in the ontology model, we must first have a clear idea of how context should be defined. In this thesis, we adopt an approach that combines the general

[2]http://foldoc.doc.ic.ac.uk/foldoc/index.html

idea of context and the ideas from the two views mentioned above. The two views appear to be different but actually address the same basic idea: ontologies are specifications of concepts and objects, which are commonly agreed in the most general sense, while context confines the model of a domain to a local view which can be generated by the system dynamically when situated in a particular context. Hence, we consider context as the set of entities found in a particular situation, which affects the interpretation of the model of a domain.

In addition, it is commonly agreed that the effect of context on any reasoning task is not solely dependent on the situation and the things present in the scene, but also involves the internal state [110] and subjective perspective [38] of the observing individual, we will therefore develop our idea based on this notion. We consider that contexts will cause a change in the perspective of a user or a software agent, which results in a change in the interpretation of the concepts defined in an ontology, and thereafter affects the final conclusion drawn from the facts in the knowledge base of the ontology. In the following, we will describe in details the definitions and mechanisms of the framework for modeling context in ontologies.

3.9.1 Formal Definitions

Following the general idea that context is considered as the surrounding entities which give meaning to a particular object, event or concept in question. We define a context t as a collection of propositions, objects and concepts perceived by an agent in the Semantic Web environment.

Definition 13. *A* ***context*** t *is a three-tuple* $\langle N_r, N_c, N_i \rangle$*, where* $N_r \subseteq R$*,* $N_c \subseteq C$ *and* $N_i \subseteq I$*.*

This definition is concise and flexible, and it adheres to our view on context discussed in the previous section. For example, the context of cooking may consist of "knife", "saucepan", "oven", "food", "vegetables", etc. These terms can refer to either abstract concepts or individual objects. In other words, context is a collection of entities which one may encounter in that situation.

When an agent in the Semantic Web perceives, or situates, in a particular context, the agent forms a certain perspective, or there will be a change in the internal state of the agent. A perspective can be considered as a certain viewpoint on the concepts and objects encountered by the agent, as Lakeoff and Johnson comment on the effect of context, "*we make a choice of categories because we have some reasons for focusing on certain properties and downplaying others.*" [62].

Here, we define perspective as a viewpoint from which an agent assigns different weights to properties in concepts as a way to reflect its foci on certain properties. Formally, perspective is a mapping which maps the set of two-tuples, consisting of a concept and a property, to a real number between 0 and 1.

Definition 14. *A* ***perspective*** v *is a mapping from the set* $C \times P$ *into the set of real numbers in the range 0 to 1, which represents the weights of the properties in the concepts.*

$$v : C \times P \longrightarrow [0,1]$$

A perspective of an agent actually decides the importance of every property in the concepts. Since a change in the current context will result in a change in the current perspective held by the agent, the overall effect is that in different contexts the weights of properties in concepts will be different. In order to estabish a relation between the set of contexts and the set of perspectives, we define the function *View* for this purpose.

Definition 15. *Let* T *be the set of contexts and* V *be the set of perspectives, the function* **View** *is a mapping from* T *to* V.

$$View : T \longrightarrow V$$

Intuitively, that a certain perspective is chosen when situated in a certain context is related to past experiences. Therefore, the function $View$ can probably best be obtained by using some learning algorithms, which gradually discovers the interrelations between individuals, concepts and properties. Through the learning process, properties that are usually associated with a certain context will be weighted higher and higher in the according perspective. Since in this thesis we focus on the overall framework of modeling context, we assume that this function is properly defined at the time being, and leave the development of a mechanism to obtain such function as one of the future research directions that can further enhance this model.

3.9.2 Contextualization of an Ontology

After an agent has chosen a perspective according to the perceived context, the agent forms a *contextualized* ontology by applying the weights to the properties in concepts. In this way, the original ontology is said to be *contextualized* by the perspective held by the agent. With reference to [42] and [41], this process of contextualization can be formalized by a set of interpretations, similar to the interpretation in Description Logics [10].

In Description Logics, formal semantics of concepts are defined by using an interpretation $\mathcal{I}$ [11], which consists of a domain and an interpretation function. In our framework, a contextualized ontology is constructed in a similar way. According to the agent's chosen perspective, a certain interpretation of the concepts and properties in the ontology is used. The interpretation assigns to each concept a characteristic vector which contains the corresponding weights of the properties according to the perspective held by the agent.

Definition 16. *An* ***interpretation*** m *consists of a domain* Δ

and an interpretation function $\mathcal{I}$:

$$m = \langle \Delta, \mathcal{I} \rangle$$

where Δ refers to the domain and $\mathcal{I}$ is an interpretation function.

In using different interpretations to realize contextualization of an ontology, we adopt a constraint mentioned in [42, 41], that the domain of interpretation is the same under different interpretations. This is because we are interested in different interpretations (categorizations) of the same set of individual objects in different contexts. The constraint is given formal below.

$$\forall m_i, m_j \in M, i \neq j, \Delta_i = \Delta_j = I$$

where M is the set of interpretations. In other words, the domain of interpretation is the same as I, the set of all individual objects in the domain.

The interpretation function $\mathcal{I}_i$ of an interpretation m_i is a function that maps each concept $x \in C$ to a fuzzy subset of I, and assigns a characteristic vector c_x to the concept x. With this mechanism, the weights of properties assigned by the perspective of an agent can be realized in the characteristic vector of a concept.

With a different characteristic vector in different contexts, the degree of likeliness and degree of typicality of an individual object with respect to a concept will also be different due to the different weights of the properties. In addition, the extent to which a concept is similar to another will also be different.

We define a mapping *Select* which maps the set of perspectives into the set of interpretations. Since a perspective assigns weights to different properties, there is sufficient information for determining the characteristic vectors of the concepts in the ontology. Therefore, this function can be readily obtained.

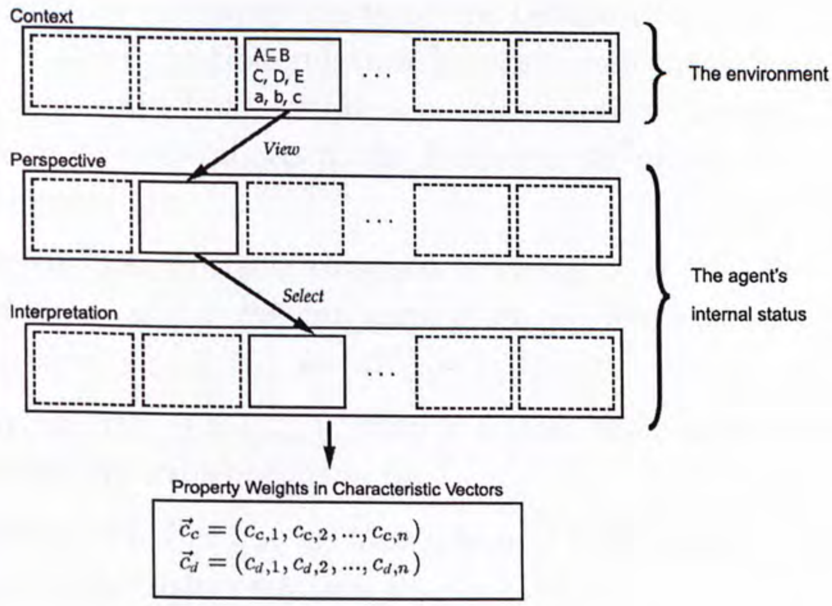

Figure 3.1: Context and Contextualization of an Ontology

Definition 17. *Let V be the set of perspectives and M be the set of interpretations,* **Select** *is a mapping that maps V into M.*

$$Select : V \longrightarrow M$$

Figure 3.1 presents an overview picture of the process of contextualizing an ontology.

3.9.3 Contextualized Subsumption Relations, Likeliness, Typicality and Similarity

A hierarchy of concept can be constructed by determining concept subsumption relations. Concept subsumption is determined by checking the weights of properties in the characteristic vectors of the two concepts, as defined by Definition 4. However, these subsumption relations will become dynamic when we take context into account. This is because different contexts will constitute different distributions of property weights, which will then affect the subsumption relations between concepts. In particular, a subsumption relation between concept x and y, say $x \sqsubseteq y$, may only hold within a certain context. Hence, *Definition 4* can be generalized to the following definition in a contextualized ontology.

Definition 18. *For two concepts x and y, x is said to be* ***subsumed by*** *y under the interpretation m_t, denoted by $x \sqsubseteq_{m_t} y$, if and only if $c_{x,j} \geq c_{y,j}$ for all $j = 1, 2, ..., n$.*

Definition 19. *If $x \sqsubseteq_{m_t} y$, then x is said to be a* ***sub-concept*** *of y under the interpretation m_t.*

Definition 20. *If $x \sqsubseteq_{m_t} y$, then y is said to be a* ***super-concept*** *of x under the interpretation m_t.*

Hence, under different context, the subsumption relations between concepts may be different. With this mechanism, the ontology is able to handle concepts which can be categorized into different categories according to the current context.

In addition, as there are changes in the property weights in concepts, the measures of likeliness, typicality and similarity will also change accordingly. This is because the calculations of the three measures all depend on the characteristic vectors of the concepts. In other words, an object's likeliness and typicality, as well as the similarity of a concept to another, are dependent on context. We make use of the following notations to represent these contextualized measures with respect to a context t.

$$\begin{aligned} \text{Likeliness}: &\quad \lambda_{x,t} : I \longrightarrow [0,1] \\ \text{Typicality}: &\quad \tau_{x,t} : I \longrightarrow [0,1] \\ \text{Similarity}: &\quad \sigma_{x,t} : C \longrightarrow [0,1] \end{aligned}$$

Table 3.1: Contextualized Likeliness, Typicality and Similarity

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□ **End of chapter.**

Chapter 4

Discussions and Analysis

Given the formal model of ontology described in Chapter 3, it is interesting and worthwhile to discover more about its characteristics and properties, and discuss what the benefits as well as limitations of using such model are. In this chapter, we discuss and perform analysis on the characteristics of the model. In particular, we will discuss the properties of the formal model based on the definitions and axioms described before, investigate the differences between likeliness and typicality of an individual in a concept, and compare the proposed ontology model with other related works so as to identify the advantages and limitations of our proposal.

4.1 Properties of the Formal Model for Fuzzy Ontologies

Likeliness measures the extent to which an individual is considered as an instance of a concept. It is interesting to note that the likeliness of an individual in a certain concept is related to that in the sub-concepts or the super-concepts of that particular concept. Based on the definitions and axioms described, we arrive at the following theorems concerning the degree of likeliness of an individual in a concept, its sub-concepts and its super-concepts.

Theorem 4.1. *For two concepts x and y and an individual a, if $x \sqsubseteq y$, then $\lambda_x(a) \leq \lambda_y(a)$.*

Proof. Firstly, by Definition 4, if $x \sqsubseteq y$ we have $c_{x,i} \geq c_{y,i}$. We consider three situations while giving the proof of this theorem.

In the first case, assume that individual a does not possess all of the defining properties of y, and thus does not possess all of those of x since $x \sqsubseteq y$. Hence, $\lambda_x(a) = \lambda_y(a) = 0$, according to Axiom 2.

In the second case, assume that in the property vector $\vec{p}_a$ there are elements $p_{a,j}$ such that $p_{a,j} > 0$ for those i's that $c_{x,j} > 0$ and $c_{y,j} > 0$. Then by Axiom 4, since $c_{x,i} \geq c_{y,i}$ for all $i = 1, 2, ..., n$, $\lambda_x(a) \leq \lambda_y(a)$.

Finally, assume that in the property vector $\vec{p}_a$ there are elements $p_{a,j}$ such that $p_{a,j} = 1$ for those i's that $c_{x,j} > 0$ and $c_{y,j} > 0$. Then by Axiom 5 we have $\lambda_x(a) = \lambda_y(a)$.

Combining the above three cases, we have $0 \leq \lambda_x(a) \leq \lambda_y(a)$ if $x \sqsubseteq y$. □

This theorem states that if concept x is subsumed by concept y, an individual's likeliness in x must always be less than or equal to that in y. This result is in fact a very intuitive and natural one. From a theoretical point of view, a sub-concept generally imposes more requirements on an individual for it to be considered as an instance, because a sub-concept is more specific than its super-concepts. Hence, if an individual satisfies the requirements of being considered as an instance of a particular concept, it must also satisfy the less restricted requirements imposed by its super-concepts. Therefore, the likeliness of an individual a in concept y will be larger than that in concept x if x is subsumed by y.

From the above theorem, we can further obtain the following two corollaries, which concern the relations between likeliness of an individual object in a concept and that in the sub/super-concepts of this concept.

Corollary 4.2. *For a concept x and an individual a, if $\lambda_x(a) = 0$, then $\lambda_{m_i}(a) = 0$ for all $m_i \in S$, where S is the set of sub-concepts of x.*

Proof. Firstly, we note that $\lambda_x(a) \geq 0$ by definition. By Theorem 4.1, if $m_i \sqsubseteq x$, then $\lambda_{m_i}(a) \leq \lambda_x(a)$. Hence, if $\lambda_x(a) = 0$, which means that $\lambda_{m_i}(a) \leq \lambda_x(a) = 0$, then $\lambda_{m_i}(a) = 0$. □

Corollary 4.3. *For a concept x and an individual a, if $\lambda_x(a) > 0$, then $\lambda_{m_i}(a) > 0$ for all $m_i \in T$, where T is the set of super-concepts of x.*

Proof. By Theorem 4.1, if $x \sqsubseteq m_i$, then $\lambda_x(a) \leq \lambda_{m_i}(a)$. Hence, if $\lambda_x(a) > 0$, then $\lambda_{m_i}(a) \leq \lambda_x(a) > 0$. □

Corollary 4.2 states that if the degree of likeliness of an individual a is zero in a concept x (not considered as an instance of x), then its degree of likeliness will also be zero in all the concepts that are sub-concepts of x (not considered as an instance of all the sub-concepts of x). From a theoretical point of view, if individual does not possess the properties required to be judged as an instance of a concept, then it is natural that it will not satisfy the requirements of being considered an instance of the sub-concepts of this concept, because sub-concepts impose more requirements. Intuitively, this is easily understood. For example, if a certain object is not an instance of musical instruments, then naturally it is also not an instance of pianos, violins or any other musical instruments.

Corollary 4.3 states that if the degree of likeliness of an individual a is greater than zero in a concept x (possesses all the defining properties of the concept), then its degree of likeliness will also be greater than zero in all the concepts that are super-concepts of x. This is actually a very natural relationship of an individual's membership in a concept and its super-concepts. If an individual satisfies all the requirements of being considered as an instance of a concept, it must also satisfy the requirements of being considered as an instance of the super-concept of this concept. This is because super-concepts are more general and are defined by fewer properties. For example, if a certain animal is an instance of sparrows, then naturally it is also an instance of birds or an instance of vertebrates.

Furthermore, we examine another property of the proposed model which is found in the measure of typicality of individuals in concepts. Based on the definitions of prototype vectors and the axioms which a typicality function should satisfy, we have the following theorem concerning the typicality of individuals in a concept hierarchy.

Theorem 4.4. *In a concept hierarchy in which every concept has only one immediate sub-concept and one immediate super-concept, for two concepts x and y and an individual a, if $x \sqsubseteq y$, then $0 \leq \tau_x(a) \leq \tau_y(a)$.*

Proof. According to Definition 9, the construction of the prototype vector of a concept is given by

$$\vec{t}_x = \frac{1}{|S|} \sum_{s \in S \cup \{x\}} \vec{c}_s$$

and therefore each element in the prototype vector is given by

$$t_{x,i} = \frac{1}{|S|} \sum_{s \in S \cup \{x\}} c_{s,i}$$

Assume that every concept has only one immediate sub-concept and one immediate super-concept. By Definition 4, if $x \sqsubseteq y$, we have $c_{x,i} \geq c_{y,i}$. If we label the concepts from the root of the concept hierarchy, i.e. the most general concept, to the most specific concept by m_k, we have the following inequality,

$$\frac{c_{m_1,i} + c_{m_2,i} + \ldots + c_{m_k,i}}{k} \leq \frac{c_{m_1,i} + c_{m_2,i} + \ldots + c_{m_k+1,i}}{k+1}$$

Hence,

$$t_{m_1,i} \leq t_{m_2,i} \leq \ldots \leq t_{m_k,i}$$

By Axiom 10, we conclude that if $x \sqsubseteq y$, then $0 \leq \tau_x(a) \leq \tau_y(a)$. □

This theorem states that in a concept hierarchy in which each concept has at most one immediate super-concept and one immediate sub-concept, if concept x is subsumed by concept y, an individual's typicality in x must always be less than or equal to that in y. We restrict ourselves to such a simple concept hierarchy when discussing this theorem, because when the number of sub-concepts is large, the values of the elements in the prototype vector will vary greatly, making the analysis very difficult.

With Theorem 4.4, we can further obtain the following corollaries.

Corollary 4.5. *In an ontology in which every concept has only one immediate sub-concept and one immediate super-concept, for a concept x and an individual a, if $\tau_x(a) = 0$, then $\tau_{m_i}(a) = 0$ for all $m_i \in S$, where S is the set of sub-concepts of x.*

Proof. Firstly, we note that $\lambda_x(a) \geq 0$ by definition. By Theorem 4.4, if $m_i \sqsubseteq x$, then $\tau_{m_i}(a) \leq \tau_x(a)$. Hence, if $\tau_x(a) = 0$, which means that $\lambda_{m_i}(a) \leq \lambda_x(a) = 0$, then $\lambda_{m_i}(a) = 0$. □

Corollary 4.6. *In an ontology in which every concept has only one immediate sub-concept and one immediate super-concept, for a concept x and an individual a, if $\tau_x(a) > 0$, then $\tau_{m_i}(a) > 0$ for all $m_i \in T$, where T is the set of super-concepts of x.*

Proof. By Theorem 4.4, if $x \sqsubseteq m_i$, then $\tau_x(a) \leq \tau_{m_i}(a)$. Hence, if $\tau_x(a) > 0$, then $\tau_{m_i}(a) \leq \tau_x(a) > 0$. □

With the assumption that every concept has only one immediate sub-concept and one immediate super-concept, Corollary 4.5 states that if the degree of typicality of an individual a is zero in a concept x, then its degree of typicality will also be zero in all the concepts that are sub-concepts of x. In addition, Corollary 4.6 states that if the degree of typicality of an individual a is greater than zero in a concept x, then its degree of typicality will also be greater than zero in all the concepts that are super-concepts of x. Both results are similar to those we have discussed about the properties of likeliness.

Theorem 4.4, Corollary 4.5 and Corollary 4.6 are valid only when the assumption that each concept has only one immediate sub-concept and one immediate super-concept is true. We understand that this is a rather strict assumption. In fact, since calculation of typicality of individual objects depends on the prototype vector of the concept in question, and the values of the elements in this prototype vector in turn depend on both the number of sub-concepts and the values of the elements in the characteristic vector of these sub-concepts, which can vary in a great range. It is therefore difficult to analyze the properties of typicality in general situation.

4.2 Likeliness and Typicality

Besides the above properties, we further discuss the relationship and characteristics between the two measures of membership grade, likeliness and typicality.

Both likeliness and typicality measure the membership grade of an individual object in a concept. However, as we have discussed in Chapter 2, they are quite different in nature. Likeliness measures the extent to which an individual object is considered as an instance of a concept according to some pre-defined conditions, while typicality measures how typical or how representative an individual is to a concept. Due to their differences, it is not surprised that the degree of likeliness and the degree of typicality of an individual object in a particular concept are not related to each other. In fact, there are actually situations in which the degrees do not agree to each other even for the same individual when referring even to the same concept.

On one hand, an object can attain high degree of likeliness but low degree of typicality in a certain concept. Such example has already been described in the previous chapter. A particular ostrich, though undoubtedly considered as a bird, attains relatively low degree of typicality in the concept "Bird". The reason of such outcome is that the object does not possess the properties that are very common among the sub-concepts of the concept involved.

On the other hand, an object can also attain zero degree of likeliness but still a non-zero degree of typicality in a certain concept. In such case, the object is not classified as an instance of the concept. However, since it shares some common properties with the prototype of the concept, it attains a positive value in typicality. This actually reflects many real situations in which people consider some objects as members of a particular concept, which by definition this is not correct. For example, some people tend to think that a bat is sort of a bird [36], or that a whale is sort of a fish.

From these two examples, we can see that likeliness and typicality are different in nature, and are not necessarily related to each other. In addition, as we can see from these two examples, the model proposed in this research can model many real cases effectively. While likeliness reflects the membership grade of an object in a concept according to the definition, typicality provides an alternative which reflects the psychological belief in the human thinking process.

In addition, it is worthwhile for us to discuss which of the two measures, likeliness and typicality, we should use to judge the membership of an individual object under different situations.

Basically, likeliness is an extension of the traditional way of modeling concepts as crisp sets. As we move on to model vague concepts or concepts without clear boundaries, likeliness provides a measure which more clearly reflects the degree to which the data instances in the ontology are classified to these concepts. For example, we may be interested in "senior employees who have worked in the company for a long period of time", "flowers with large petals and red in color", or "restaurants that are close to the railway station and not expensive". All these concepts – *long period of time*, *large*, *red*, *close*, *expensive* – imply that likeliness is essential in giving us an account of how each individual object in the ontology satisfies these requirements. Likeliness gives us an idea on which objects are classified as instances of a concept, and at the same time which are more likely or satisfy the requirements of being an instance to a greater extent.

On the other hand, the measure of typicality provides an alternative mechanism to order individual objects in a way that is closer to human thinking and psychological belief. In some situations in which every individual object satisfies the basic requirement of being an instance of a concept, it may be difficult to sort the objects by their degrees of likeliness (which may all be equal to 1). However, human users may still want the individual objects to be sorted based on their representativeness or typicality. In such situations, the measure of typicality can be used. In addition, an object does not need to be an instance of a concept (with degree of likeliness greater than zero) for it to be considered as typical. This is because typicality is calculated based on matching the properties of the prototype and the object. As a result, by measuring the typicality of individual objects in concepts, some other relevant objects can also be obtained in the reasoning process.

Hence, the two measures of membership provided make this formal model of ontology much more flexible in determining the membership of individual objects. Based on the desirable outcome or the current situation, either likeliness or typicality can be used.

4.3 Comparison between the Proposed Model and Related Works

The formal model of ontology proposed in this thesis provides a greater flexibility for modeling concepts, properties and individual objects in a domain. In this section, we give some discussions on the comparisons between our model and existing models found in literature. To facilitate the following discussions, we divide the existing models into the following four groups based on their characteristics:

1. Traditional Ontology Models
2. Fuzzy Ontologies and Description Logics
3. Ontologies Modeling Typicality of Objects
4. Ontologies Modeling Context

4.3.1 Comparison with Traditional Ontology Models

Traditional ontology models, such as classical Description Logics [10], DAML+OIL [50] and OWL [74], treat concepts as sets of individual objects. An object is considered as either an instance or a non-instance of a concept. More complex concepts are constructed by using set operations such as intersections or unions on the existing concepts. One major limitation of these ontology models is that they are not able to model fuzziness of concepts. Ontology engineers are not able to specify concepts such as "hot", "expensive" or "large" in these ontologies.

Our proposed ontology model incorporates fuzzy set theory to handle fuzziness of concepts. In this model, properties in a concept are weighted according to their importance to the definition of the concept. Moreover, properties possessed by individual objects are described by degrees with values in the range of 0 to 1. Based on these values, the measure of likeliness is used to reflect the extent to which an object is considered as an instance of a concept. Thus, this model allows concepts, properties and individual objects to be modeled in a more flexible way. With entities in the ontology defined in this way, we have more information when we carry out reasoning tasks.

4.3.2 Comparison with Fuzzy Ontologies and DLs

There are quite a number of proposals on fuzzy ontologies and fuzzy Description Logics as mentioned in Chapter 2. For example, there are models which incorporate fuzzy set theory into ontologies for medical document retrieval [82] or multilingual information retrieval [30]. There are also Description Logics which provide formal reasoning procedures for fuzzy concepts [105, 106]. There are also attempts to model fuzzy concepts in ontology languages such as OWL [103].

Compared with these ontology models, our model has both advantages and disadvantages. First of all, fuzzy Description Logics provide a rather comprehensive reasoning procedures for reasoning about implicit knowledge or checking of satisfiability of statements. In addition, some models improve the expressiveness of fuzzy Description Logics such as by adding fuzzy hedges [47]. Moreover, proposals on fuzzy ontology languages provide formal syntax for ontology engineers to define concepts and properties in a symbolic way. In comparison to these works, the model proposed in this thesis is a relatively preliminary work which does not yet has a sound and complete reasoning procedure. However, our work does incorporate novel ideas and is able to solve problems that cannot be easily dealt with in existing models.

One advantage of our model is that we distinguish the measure of likeliness from the measure of typicality. Likeliness is used to model fuzziness of concepts, which provides similar functions as the aforementioned models. In addition to this, our model has another measure of membership, typicality, to reflect how representative or typical an individual object is with respect to a concept. As we have discussed in Chapter 2, likeliness and typicality are two different measures, and typicality is a rather psychological measure which does not necessarily correspond to matching the definitions of the concepts. It has been pointed out that modeling such psychological aspect of categorization is desirable and it allows the reasoning process to be more realistic and intuitive [108, 114]. Besides, such ordering of objects by their representativeness or typicality finds applications in quite a number of areas, such as information retrieval, information management or agent communications. Since typicality is not formalized in the mentioned fuzzy ontologies and fuzzy Description Logics, it is less likely that they can provide the expressiveness and flexibility available in our model.

4.3.3 Comparison with Ontologies modeling Typicality of Objects

In Chapter 2, we mentioned two models of ontology [35, 109] that provide mechanisms to specify typical properties of a concept in an ontology. In fact, their mechanisms are rather similar in that they allow ontology engineers to specify the typical or allowed range of values of the properties of a concept. By checking the values of the properties of an object, one can determine whether this object is a typical instance of the concept.

Compared with these two models, the model of ontology proposed in this thesis is more comprehensive in the sense that we formalize the mechanism to form prototypes and calculate the degree of typicality based on matching the properties of an individual object and that of the prototype of a concept. This is different from modeling typicality by simply adding slots to properties for typical ranges. In addition, we do not specify a single function for calculation of typicality, but rather formulate a set of axioms that such function should satisfy. This provides greater flexibility for calculating typicality in different applications. In addition, a very important difference between our model and the two models mentioned above is that in those two models the typicality of an object can be judged only after it is identified as an instance of a concept, while this is not necessary in our model (note that likeliness and typicality are two independent measures). Hence, our model is more flexible and provides more possibilities for the system to discover typical objects.

4.3.4 Comparison with Ontologies modeling Context

As we have investigated in Chapter 2, while context has been studied from a logical aspect for quite a long time, there are only a few attempts [42, 41] that try to investigate and formalize the effect of context on categorization. However, these works only provide a framework that allows one to specify different subsumption relations in different context, but do not further investigate how context changes the interpretation of concepts, properties and individual objects in an ontology. Compared to these works, the framework for modeling context in our proposal is much more flexible.

With our framework for modeling context, it is not necessary to specify explicitly which subsumption relations are true in a certain context. Instead, our proposal provides a framework for the interaction between the current context and the perspective held by an agent in the Semantic Web. Different contexts results in a different contextualized ontology, and different subsumption relations between the concepts in the ontology is the result of contextualization. In addition, our framework is also able to model the fact that typicality of individual objects in concepts is context-dependent. When there is a change in context, the property weights in the concepts will also change, and therefore there will be a different prototype vector for each concept, and the degree of typicality will be different.

4.3.5 Limitations of the Proposed Model

While we have discussed the advantages of the formal model of ontology proposed in this thesis, we also realize certain limitations of this model.

Firstly, although the extension allows properties to be weighted so as to give more flexibility in defining a concept, the weights nevertheless put extra burden on the construction of ontologies. It has been recognized that constructing an ontology requires substantial effort [40]. As the number of concepts and properties increases, ontology construction becomes a more tedious and time-consuming task. In view of this, various methods have been proposed to generate an ontology automatically (e.g. [31, 71, 76, 25]). In our proposed model, this issue is further complicated by the weights of the properties in concepts. Therefore, some efficient methods for constructing an ontology according to this model should be available.

Moreover, the function of drawing inferences in an ontology is as important as modeling concepts and properties. In this thesis, we propose a formal model for fuzzy ontologies, but a sound and complete reasoning procedure in such an ontology for reasoning about concepts and determining satisfiability as in fuzzy Description Logics is needed if ontologies based on this model are to be used to provide reasoning services.

In addition, we model properties and concepts in this formal model of ontology under the assumption that every property is independent of each other. However, there are quite a number of situations in which properties are related to each other [100, 28]. For example, some properties are highly correlated to each other, and they appear together in a concept definition very frequently, while some properties are complements to each other, and they seldom or never appear in a concept definition at the same time. Therefore, the model proposed here tends to simplify this issue and is expected to be enhanced in the future.

4.4 Significance of Modeling Likeliness, Typicality and Context in Ontologies

In this thesis, we argue for the advantages of modeling likeliness, typicality and context in ontologies. Although we understand that the formal model for fuzzy ontologies proposed here has certain limitations which require further studies of the topic, we have presented the advantages of this model over other existing models. In this section, we highlight the significance of modeling likeliness, typicality and context in ontologies.

Firstly, likeliness measures the extent to which an individual object is considered as an instance of a concept. This is used to model the fact that many concepts in real life do not have well-defined and clear enough boundaries. If we do not model fuzziness of concepts in ontologies, we cannot avoid concept definitions from being overly simplified. Concepts such as "large", "expensive", "distant" and "hot" are probably best be modeled by fuzzy set theory so that there is a gradual change from membership to non-membership. If we do not have likeliness in the model, the results of the reasoning process provided by the ontologies will be unrealistic or inappropriate. On the other hand, by modeling fuzziness in ontologies, users are able to specify their requests in terms of some fuzzy concepts which are more commonly used in daily life, thus making the information system more user-friendly.

In addition to likeliness, the measure of typicality of objects is provided in our model. As we have discussed in Chapter 2, the nature of typicality is different from that of likeliness, but is also an important issue when we improve ontology models. Typicality is a very important phenomenon, it shows that human do not always reason according to the known definitions of concepts. If information systems aim at providing better services to human users, they should take into account this aspect of human thinking, and produce results that are closer to the expectations or typical thinking of human users. One important aspect of typicality is that once an individual object is similar enough to the prototype of a concept, it is considered as a typical member, no matter it is really an instance of the concept or not. Moreover, even though an individual object is not an instance of a concept, it may possess some properties which make it be considered as a member of the concept with non-zero typicality. These two aspects allow the system to discover as many relevant answers to reasoning tasks as possible. The example we are going to discuss in the next chapter illustrates this advantage.

Finally, the modeling of context in our model is also essential to the performance of an ontology. Typicality offers quite a number of benefits as mentioned above. However, one important characteristic of typicality is that it is context-dependent [13, 93]. Considering again the example mentioned in the introductory chapter, a chicken is more typical when we mention a barnyard, but a robin is more typical of a bird in general. As a further example, an expensive restaurant is typical in a city of high living standard, while it is not typical when we are talking about restaurants in a school campus. Hence, context is closely related to the degree of typicality. In addition, modeling context also allows an ontology to be sensitive to change in the current situation in which certain reasoning tasks are performed. This will enable the ontology to provide answers that are more appropriate and more specific to the current setting.

4.5 Potential Application of the Model

Ontologies have wide applications in the Semantic Web, multi-agent systems, information retrieval systems, etc. The formal model of ontology proposed in this thesis is designed to improve knowledge representation in ontologies so as to enhance their performance in the above applications. One of the applications of this model is to provide measures of relevance in information retrieval in the Semantic Web.

4.5.1 Searching in the Semantic Web

The Semantic Web is a technological movement towards a more structured Web in which resources are described by ontologies and are machine-readable, so that software agents can access these information automatically, resulting in more efficient and effective information processing. With ontologies, searching information and resources from the Web will become much more efficient and effective because software agents are able to understand the semantics of the resources on the Web.

Currently, searching in the Web involves retrieval of web documents, which are usually text documents marked up in

HTML.[1] In the Semantic Web, however, searching of information is actually an action of querying an ontology to retrieve resources which satisfy some conditions [104]. Consequently, all resources retrieved are relevant to the query, unlike in traditional information retrieval that relevance of retrieved documents has to be determined by various methods, such as similarity between the documents and the search terms [58]. However, although querying in the Semantic Web always returns relevant answers, we notice several challenges and limitations.

Firstly, even though all retrieved resources from the Semantic Web are relevant to the query submitted, users usually still want to have the answers to the query sorted or ranked. When resources satisfy all the required conditions, it does not necessarily mean that they are equally wanted. People tend to think that some items are more typical or representative, and would therefore prefer to have access to the more typical items first. Moreover, given the large amount of resources available in the Semantic Web, it is beneficial to have a ranking method for the query results, and currently only very few projects (e.g. [104]) have focused on this issue.

The second problem that we want to address is that since query results are returned by a reasoning process, any resource that does not match exactly the required conditions in the query will not be returned. However, in some domains, such as searching for resources about fishes kept in an aquarium, user may not only be interested in fishes, but may also want to access information about other fish-like marine animals such as dolphins and whales, which strictly speaking are not classified as fishes. In other words, the problem is that resources that may be relevant to the query but do not fulfill all the conditions are never returned. Since we believe that using semantic information to enhance information processing should not impose more restric-

[1] http://www.w3.org/MarkUp/

tions to querying in the Web, we think that there should be some mechanisms in the ontologies to allow some other relevant information to be returned.

4.5.2 Benefits of the Formal Model of Ontology

The formal model of ontology in this thesis is able to provide a better mechanism for information retrieval in the Semantic Web. In particular, the measure of typicality provides a new method for the determination of the relevance of the query results. In fact, the proposed model presents several possibilities to enhance determining relevance of instances in query evaluation in the Semantic Web.

Firstly, instances returned as answers for a query can be ordered according to their degrees of likeliness. This actually returns all instances that satisfy the requirements of the concept in the query, but with extended ability to handle fuzzy concepts. With a ranking algorithm based on the likeliness of individual objects, users or agents will be able to get access to instances that most likely classified to the concept in the query. Secondly, returned instances can be ordered by using their degrees of typicality. In this way, some instances that do not satisfy all the requirements but may be considered as relevant will still be accessible to the user. This provides more relevant answers to the query but at the same time keeps the results to be as relevant as possible. In addition, typicality is calculated based on the representativeness of the object, hence the ranked result will appear closer to the expectation of the user. Lastly, the formalization of context in our model also allows users or agents to focus on certain properties as the context varies, resulting in more appropriate answers to the queries.

□ **End of chapter.**

Chapter 5

Conclusions and Future Work

In this final chapter, we present a summary of our research work reported in this thesis, and give conclusions of the investigations and discussions on the formal model for fuzzy ontologies carried out in previous chapters. We also discuss the possible future research directions of the work reported in this thesis.

5.1 Conclusions

This research is motivated by the limitations of existing ontology models as well as by many desirable features of the Semantic Web which have not yet been fully realized. We start this research by a thorough investigation on existing ontology models, their limitations and the possible ways of improving knowledge representation in the Semantic Web.

There are several major disadvantages of existing ontology models, including the inability to handle fuzzy concepts, the lack of formal methods for measuring typicality of individual objects, and the absence of a model that deals with the effect of context on various reasoning tasks. This thesis investigates these challenges, looks into research in cognitive psychology for insights and inspirations on how ontologies can be improved, and proposes a formal model of ontology to tackle these problems.

The model proposed in this thesis cultivates several innovative ideas:

1. We distinguish between likeliness and typicality, which are both important measures of membership of individual objects, but with different nature and mechanisms, and both are important and desirable to be formalized in an ontology model.

2. We use likeliness to measure the extent to which an individual object is considered as an instance of a concept, and use typicality to measure the representativeness of an individual object with respect to a concept. These treatments are supported by research in the field of cognitive psychology.

3. We formulate a set of axioms for functions for calculating likeliness and typicality. This provides useful guidelines but does not limit the flexibility of using different functions to calculate these two measures.

4. We adopt the ideas of measuring similarity in cognitive psychology into our proposed model, and formulate a set of axioms that governs the behaviour of a similarity function. Such function is useful in discovering similar concepts, which will be important in applications such as ontology matching and information sharing among software agents.

5. We propose a method to formalize context in an ontology, and design a mechanism for changing the interpretation of concepts and properties defined in an ontology according to changes in context. This is essential because the measures of typicality and similarity are found to be context-dependent.

We understand that the proposed model has several limitations. The model still requires a sound and complete reasoning algorithm for a system to reason about the concepts defined in the ontology. Some more complicated issues such as how correlations between properties can be represented in this model are yet to be investigated. Moreover, the introduction of property weights and degrees of possession of properties in the model incurs extra burden on the construction of ontologies. In other words, an automatic or at least semi-automatic algorithm for generating an ontology according to this model is very much desirable. Nevertheless, it is clear that the ideas proposed and discussed in this thesis are significant to the improvement of ontologies and knowledge representation in the Semantic Web. We emphasize on the use of fuzzy set theory and theories of concepts from cognitive psychology to enhance the representation and modeling of concepts and properties, thus allowing the knowledge stored in the ontology to be more realistic and close to human thinking, which will in the end benefit various services in the Semantic Web. We also expect this research to inspire further investigations on how ontologies can be improved in the future.

5.2 Future Research Directions

There are actually quite several issues stemming from the research work described in this thesis.

The first issue is that, as we have mentioned in previous sections, a formal, sound and complete reasoning procedure should be developed to provide formal reasoning capabilities in the model. In other words, this issue concerns with how to realize the formal ontology model in knowledge representation formalism such as description logics. This, together with the membership measures of likeliness and typicality, the formal method for measuring similarity, and contextualization of ontologies proposed in this thesis, will provide a comprehensive ontology model for knowledge representation which enable various services in the Semantic Web.

Another issue that emerges from this research is the extra burden put on the process of constructing or generating an ontology according to the proposed model. The model allows properties to be weighted according to their importance to the definition of a concept, but this at the same time requires more effort to construct an ontology as the number of concepts and properties increases. Hence, one of the future research directions is to investigate how property weights can be determined more efficiently. One possibility is to develop automatic or at least semi-automatic ontology generating algorithms. For instance, [45] proposes a method for constructing Bayesian networks by combining knowledge from domain expert and information from a small data collection. Similar method may be useful in ontology learning.

In addition, there are still a number of issues from cognitive psychology which can be used to enhance ontology and knowledge representation in the Semantic Web. In particular, as we have mentioned before, and it is also intuitively obvious that properties of concepts are usually correlated to each other. For example, if we know that an object has wings, then it is very probable that this object can fly. There are actually empirical findings in cognitive psychology (e.g. [100, 28]) that people do make use of this kind of information in reasoning and cognitive tasks. As a future research direction, we can further investigate this issue and improve the proposed model so that information of correlations between properties can be modeled in ontologies. Moreover, the model of context proposed in this thesis is actually a rather preliminary framework, and requires further development and enhancement. In particular, the framework requires a learning algorithm, or other methods, to establish the function *View*, which is used by agents to map a particular context to a perspective.

Finally, effort can be put on developing the model of ontology into a practical knowledge representation model for enabling various services in the Semantic Web. For example, as we mentioned in the previous chapter that it has the potential to enhance searching in the Semantic Web, we can further develop the model and incorporate into it a complete Semantic Web searching mechanism so as to provide a better searching system for users in the Semantic Web. This will provide users with the flexibility of ranking searching results by likeliness, typicality or similarity, as well as the benefits of context-sensitive interpretation of concepts and properties.

To conclude, we hope that the research work described in this thesis will bring insights and inspirations to the field of ontological engineering and knowledge representation in the Semantic Web. By incorporating ideas from cognitive psychology, we reveal the different possibilities to enhance and improve the performance and flexibility of ontologies. We hope that the proposed model of ontology can be further developed in the directions mentioned above, and finally give birth to more fruitful research results that will ultimately accelerate the development of the Semantic Web and information sharing in general.

□ **End of chapter.**

Publications

- C. M. Au Yeung and H. F. Leung. Formalizing Concepts in Description Logics Using a Cognitive Approach. In *PRIMA 2005: Proceedings of the 8th Pacific Rim International Workshop on Multi-Agents*, Kuala Lumpur, Malaysia, 26-28 September 2005.
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